Impacts of the Low-Interest Rate Policy on the Corporate Sector

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Contents

List of Figures

List of Tables

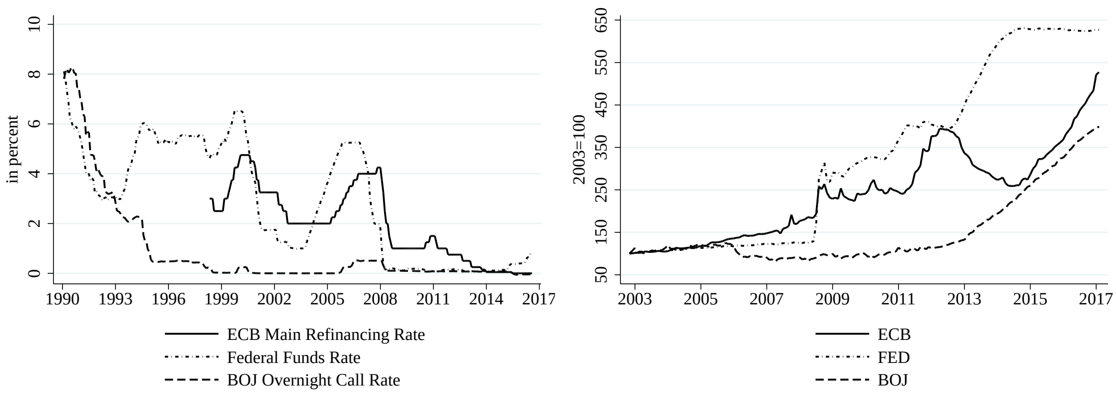
Chapter 1

Dissertation Introduction

In 2008, the world experienced the deepest and most consequential financial crisis since the 1930s. The financial turmoil and ensuing credit crunch culminated in an economic downturn that caused a historic contraction in global gross domestic product during 2009. The crisis affected developed and developing countries alike. In response to the crisis, the leading central banks cut monetary policy rates to unprecedented low levels (Figure 1.1a). They also introduced a set of non-standard monetary policy measures, such as quantitative easing, credit easing and liquidity injections (Kohn, 2010; ECB, 2010a, 2011), which inflated the central banks' balance sheets (Figure 1.1b). These measures were aimed at stabilizing financial markets, maintaining the functioning of the monetary policy transmission mechanism and improving financing conditions for the private sector.

Figure 1.1: Post-Crisis Monetary Policy

(a) Central Banks' Policy Rates **(b)** Central Banks' Total Assets



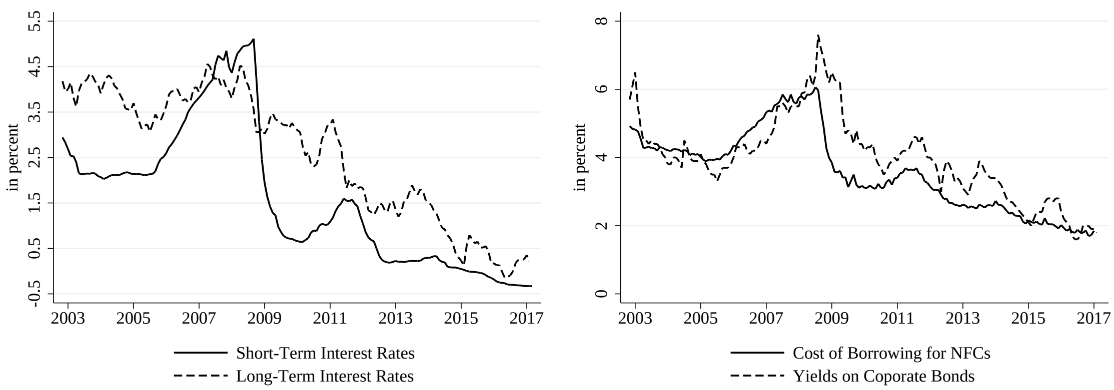
Source: ECB, Bank of Japan, Federal Reserve Bank.

It has been widely acknowledged that the immediate implementation of conventional and unconventional policy measures helped to avoid a meltdown in the global financial system. Furthermore, the IMF (2013) stated that the central banks' emergency measures prevented a much deeper recession. However, more than eight years after the outbreak of the financial crisis, many central banks – including the European Central Bank (ECB) – remain in permanent crisis mode, and ultra-loose monetary policies have become the new normal.

Owing to the continuing economic stagnation in the euro area, the ECB launched a massive asset purchase programme in January 2015. Under this programme the ECB has been purchasing private and public sector securities amounting to 60 to 80 billion EUR per month (ECB, 2017a). Furthermore, in 2014 the ECB was the first large central bank to introduce negative deposit facility rates. While the US Federal Reserve Bank announced its monetary policy normalization in 2015 and has ever since been slowly raising its policy rate (FED, 2017), the ECB continues its low-interest rate policy in response to persistently low inflation rates in the euro area.

Figure 1.2: Post-Crisis Financing Conditions in Germany

(a) Interest Rates **(b)** Cost of Funds



Source: ECB, OECD, Deutsche Bundesbank. Short-term interest rates defined as 3-month money market rates. Long-term interest rates defined as 10-year government bond yields. Cost of borrowing for NFCs defined as the weighted average of bank interest rates, charged to non-financial corporations (NFC) on new loans.

The ECB's post-crisis monetary policy has profoundly changed the financing environment of the corporate sector in the euro area, including in Germany. Short- and long-term interest rates have substantially declined to record-low levels (Figure 1.2a). This development has significantly reduced firms' financing costs. In Germany, the borrowing costs for non-financial corporations fell from 6 percent in September 2008 to 1.8 percent in March 2017. Average corporate bond yields declined from 7.6

percent in October 2008 to 1.8 percent in April 2017 (Figure 1.2b). In addition, German firms' access to finance has improved considerably. In December 2016, only 12.6 percent of German manufacturing-sector firms indicated that credit access was restricted, compared with 54 percent in September 2009.

The improvement in credit conditions – that is, in the price and availability of funds – in parts of the euro area can be regarded as a success of the ECB's conventional and unconventional monetary policy. However, the persistence of low growth in recent years has raised doubts about the policies' effectiveness. At the same time, concerns about adverse side-effects of a prolonged period of ultra-low interest rates have escalated.[1] It has been argued, inter alia, that interest rates have lost their allocation and signalling function as they are compressed towards zero or below.

Theoretically, the interest rate can be regarded as a price that balances people's willingness to consume now versus their eagerness to save for future consumption (Fisher, 1930). Because interest rates reflect people's time preferences, they guide the intertemporal and the intersectoral allocation of resources, particularly the allocation of capital. On a microeconomic level, interest rates also influence a variety of entrepreneurial decisions. Firms' investment decisions – that is, decisions about whether or not to invest, and choices between different investment projects – are influenced by the rate of interest, among others things (Fisher, 1930; Keynes, 1936). Interest rates also affect firms' financing decisions because they determine the availability and relative pricing of different types of funds (Kashyap et al., 1993; Oliner and Rudebusch, 1996b). Furthermore, interest rates can provide incentives for improving efficiency and productivity because they determine firms' costs (Hoffmann and Schnabl, 2016).

The long-term consequences of the ECB's low-interest rate policy, both for the general economy and for the corporate sector in particular, are not yet determinable, as empirical evidence for the euro area and Germany is limited. However, the Japanese economy provides a guiding example, because the Bank of Japan (BOJ) was the first central bank to set policy rates permanently to zero (Bayoumi and Collyns, 2000). In 2001, the BOJ additionally introduced quantitative easing. Nevertheless, economic growth in Japan has remained low and deflationary pressure has persisted (Schnabl,

[1] For a general discussion on the impact of quantitative easing and ultra-low interest rates see for instance Belke (2013). Dobbs et al. (2013) discuss distributional effects of the low-interest rate policy. For impacts on the banking sector see Borio et al. (2017). For impacts on insurance companies see Kablau and Weiß (2014). Freytag and Schnabl (2017) discuss the effect of the low-interest rate policy on the economic order in Germany.

2015). Instead of stimulating real growth, Japan's zero-interest rate policy has contributed to a misallocation of credit towards unproductive and highly indebted firms, thereby depressing aggregate productivity growth (Caballero et al., 2008). Two *lost decades* have in spite of massive monetary policy interventions taken a toll on the Japanese corporate sector's competitiveness.

The aim of this thesis is to analyse how the persistent low-interest rate policy in the wake of the financial crisis has affected the corporate sector. Stimulative short-term effects and long-term economic consequences are analysed. Chapter 2 evaluates the working of the interest rate channel – one of the key monetary transmission channels – with regard to its stimulating effect on German business investment in the post-crisis period. Uncertain or pessimistic business expectations have been identified as a main reason for weak business investment activities in Germany (e.g. Gerstenberger and Schwartz, 2014; Schwartz, 2015; Heymann and Schneider, 2017). Therefore, special focus is placed on the role of business expectations and the effect of those expectations on the link between interest rates and investment. Based on the neoclassical investment theory of Jorgenson (1963), the user cost elasticity of capital for a sample of 1,277 German SMEs is estimated, covering the period 2008 to 2015. The results confirm that firms were responsive to user cost changes, with the long-run user cost elasticity of capital ranging between -0.79 and -0.67. The estimates are similar to those of pre-crisis studies and indicate that declining interest rates have generally been able to stimulate business investment through changes in the firms' user cost of capital. However, the estimation results are driven by firms with positive business expectations, depicting a user cost elasticity of capital close to unity. Firms with neutral or negative expectations are shown to be unresponsive to user cost changes. The findings presented in Chapter 2 confirm the importance of business expectations for firms' investment decisions. They also reveal the limitations of low-interest rate policy as a means to stimulate the economy.

Chapter 3 analyses how declining interest rates have influenced firms' financing behaviour, in particular their demand for bank loans. On the one hand, data from peripheral countries in the euro area during the pre-crisis period indicate that a decline in interest rates can trigger a *substitution effect*. That is, firms increase their bank borrowing and substitute alternative funds (such as internal funds) with bank loans. As a result, firms' demand for bank loans increases. This can cause an acceleration in corporate-sector debt levels. On the other hand, the balance-sheet-channel literature argues that declining interest rates strengthen firms' internal financing capacity, which is defined as *income effect* (Bernanke and Gertler, 1995). If it is additionally assumed that firms follow a financial pecking order and prefer internal over external funds, a reduction in interest rates would decrease the share of bank loans in firms' financing mix. An empirical analysis based on a firm-level dataset of 8,274 German SMEs provides evidence that in the period 2005 to 2014, the income effect of declining interest rates dominated. As a result, corporate-sector bank loan demand in Germany has declined. A substitution effect (i.e. increased preference for bank loans relative to internal funds) cannot be confirmed for our observation period. Thus, the results provide evidence that a low-interest rate policy can depress corporate-sector bank loan demand.

Post-crisis productivity growth has been exceptionally weak in many countries, including Germany. It has been argued that the ECB's ultra-loose monetary policy has impeded creative destruction and market dynamics in Europe, and has thus contributed to low productivity growth (e.g. Forbes, 2015; Freytag and Schnabl, 2017). Chapter 4 presents an analysis of the impact of a prolonged period of low interest rates on the capital allocation process in a market economy. The literature is synthesised and evaluated, and at a theoretical level the post-crisis monetary policy is shown to have severely impaired the allocative function of financial institutions. Three main causes by which the efficient allocation of capital has been disrupted are identified. Firstly, the restructuring process within the banking sector has been impeded. Secondly, banks' lending behaviour has been distorted; thirdly, low borrowing costs have slowed down the restructuring process in the corporate sector. Firm-level data of SMEs are used to empirically test whether the German productivity slowdown in the post-crisis period has been caused by a less efficient allocation of capital. The results provide evidence that low-productive firms have had easier access to credit in the post-crisis period compared with the years before the crisis. This ease of access might have increased their odds of survival, and might also have lowered the incentive for those firms to increase their efficiency and productivity. The impaired reallocation and restructuring process is likely to have contributed to the low productivity growth in Germany. The findings of this chapter thus highlight the negative economic consequences of a prolonged period of ultra-low interest rates and unconventional monetary policy measures. The results lend support to the argument that exceptionally low interest rates contribute to weak economic growth.

Chapter 5 presents an analysis of how an extended period of low interest rates, combined with declining bank-loan demand from the corporate sector, affects the banking sector. This study, a joint work with Gunther Schnabl, focuses on the Japanese banking sector. It is shown how Japanese monetary policy has contributed to a growing gap between deposits and loans in the financial system, and has compressed interest margins, which were the banks' traditional source of income. Japanese banks have adjusted to the decline in their interest income by increasing their lending to the public sector and by diversifying their sources of income. Furthermore, it is shown how the Japanese banking sector underwent an increasing concentration process. For banks to remain profitable in an environment of declining interest margins, efficient utilization of resources is crucial. Therefore, using Data Envelopment Analysis, the trends for Japanese banks' technical efficiency in the period 1999 to 2015 are analysed. The effects of the low-interest rate environment and the banks' adjustment measures on the banks' technical efficiency are tested. The estimation results show that although banks' efforts to increase their efficiency has paid off – especially among regional banks, the erosion of interest margins has triggered a loss in efficiency. Furthermore, the results imply that the increased concentration process, especially among city banks, has reduced rather than increased banks' efficiency.

Chapter 2

Is the Interest Rate Channel still Working? Post-Crisis Evidence from German SMEs

Abstract

Using a unique dataset from German small and medium-sized enterprises (SMEs), we test whether pessimistic business expectations have impeded the functioning of the interest rate channel during the post-crisis period. We estimate firms' user cost elasticity of capital for the period 2008–2015, and test whether this elasticity differs for firms that hold pessimistic business expectations compared with those that hold positive expectations. Our results show that SMEs have significantly responded to changes in the user cost of capital during the post-crisis period. However, the results are mainly driven by SMEs that hold positive business expectations. Firms having neutral or negative expectations depict a much smaller user cost elasticity, which is not statistically different from zero. Our results reveal the limitations of an expansionary monetary policy, and confirm the important role that expectations play for firms' investment decisions.

2.1 Introduction

In 2008, Europe experienced the worst financial crisis since the Great Depression, which was followed by a severe economic downturn. In response, the European Central Bank (ECB) reduced monetary policy rates to unprecedented low levels and introduced unconventional monetary policy measures. The aim was to stabilize financial markets, prevent a credit crunch and stimulate the real economy (ECB, 2010b). More than eight years later, short- and long-term interest rates in the euro area are still close to zero. Despite record low interest rates, economic recovery continues to be sluggish (ECB, 2017b). The apparent inability of ever-declining interest rates to stimulate the real economy raises questions about the effectiveness of the ECB policy measures and the proper functioning of traditional monetary policy transmission channels. In this paper we present an evaluation of the functioning of the *interest rate channel* in the post-crisis period.

The interest rate channel is one of the core monetary policy transmission channels and links short-term policy rates with economic agents' spending decisions. Declining interest rates should reduce households' and firms' cost of capital, and should encourage them to consume and invest (Mishkin, 1995). However, business investment[1] in particular has recovered rather slowly in many euro area countries, including Germany (EIB, 2016). Although interest rates on loans to the corporate sector in Germany have fallen substantially since 2009 and firms' access to finance is excellent, business investment continues to be weak and has still not recovered to its pre-crisis level. Thus, cheap and readily accessible finance seems not to have provided a strong enough stimulus for business investment in Germany.

Several studies, some based on surveys among German corporations, have identified uncertainty and gloomy business expectations as main reasons for firms' post-crisis reluctance to invest (e.g. Gerstenberger and Schwartz, 2014; Schwartz, 2015; Heymann and Schneider, 2017). For the G7 economies, Banerjee et al. (2015) find that expectations of future economic conditions appear to be more important in driving business investment than the availability of low-cost finance. Such findings raise the question whether pessimistic business expectations have impaired the traditional link between interest rate and investment, thus mitigating the effectiveness of the ECB's expansionary monetary policy.

[1] In this paper we define *business investment* as gross investment in machinery, equipment and non-residential construction (EIB, 2013).

Using a unique dataset of German small and medium-sized enterprises (SMEs), the aim of this study is twofold. First, following the neoclassical investment theory pioneered by Jorgenson (1963), we estimate firms' user cost elasticity of capital for the period 2008 to 2015 to evaluate whether firms responded to interest rate changes. Thus, we contribute to the existing interest rate channel literature by focusing on the post-crisis period. Most studies that have investigated the user cost elasticity of capital among German firms have used data up to 2007 (von Kalckreuth, 2001; Harhoff and Ramb, 2001; Büttner and Hönig, 2011; Dwenger, 2014). Only Büttner et al. (2015) included data from after the financial crisis, but only up to 2012.

Second, as our dataset includes firm-specific information on sales expectations, we are able to analyse how business expectations have affected SMEs' investment behaviour in the post-crisis period. We empirically test whether firms' user cost elasticity of capital would change according to different business expectations. The results of our analysis provide insight into the causes of the restrained business investment activities in Germany in the post-crisis period.

2.2 Interest Rates and Business Investment: Conventional Wisdom

The success of the ECB's expansionary monetary policy in the post-crisis period rests on its ability to lower market interest rates, to improve economic agents' access to finance and to encourage economic agents to increase their spending. The latter particularly applies to business investment. The link between interest rates and investment has for decades been the focus of extensive research.

2.2.1 The Interest Rate Channel

That monetary policy can influence the real economy is widely accepted.[2] However, *how* monetary policy impulses are transmitted to the real economy is not as clear, and the monetary transmission process has not been called a 'black box' without reason (Bernanke and Gertler, 1995). Extensive research on monetary transmission mechanisms over the past 30 years has examined this question and has identified a complex combination of various channels.[3]

[2] Studies that have shown that monetary policy affects economic activities include Friedman and Schwartz (1963), Romer and Romer (1989), Bernanke and Blinder (1992), Galí (1992), Christiano et al. (1996), Leeper et al. (1996), Boivin et al. (2010) and Gertler and Karadi (2014).

[3] For an overview of monetary transmission channels see Mishkin (1995).

The standard monetary policy transmission channel discussed in the economic literature over the past 80 years has been the *interest rate channel*. It is the key transmission mechanism in the Keynesian IS-LM textbook model, as it connects monetary policy impulses with economic agents' spending decisions (Hicks, 1937). The model is still a standard feature in many central bank publications (e.g. Ireland, 2005; ECB, 2000, 2008, 2010b) and remains one of the core channels in macro-economic modelling (Boivin et al., 2010). Summarizing the findings of the *Eurosystem Monetary Transmission Network*, Angeloni et al. (2003) argue that the interest rate channel is the most important transmission channel in the euro area.

The transmission of an expansionary monetary policy shock to the real economy through the interest rate channel can be summarized as follows. A loose monetary policy causes a decline in nominal short-term interest rates. Assuming that wages and goods prices are sticky, a decline in nominal short-term interest rates translates into a decline in real short-term interest rates. Since long-term interest rates are the expected weighted average of future short-term interest rates, as described by the *expectations hypothesis of the term structure* (Sargent, 1972), real long-term interest rates also decline. Assuming that investment decisions are sensitive to alterations in the real long-term interest rate because of the impact on economic agents' costs of capital, investment will rise. Therefore, aggregate demand and output will also rise (Taylor, 1995; Mishkin, 1995).

From the above description it follows that the functioning of the interest rate channel is based on two key assumptions. First, monetary policy measures must be able to alter short-term and long-term market rates. This particularly applies to bank lending rates, as bank loans are the most important source of external finance for the non-financial corporate sector (EIB, 2015). Second, economic agents must react to these interest rate changes – that is, entrepreneurs will consider interest rates when making their investment decisions. In various large-scale macro-econometric models[4] used for forecasting and policy analysis at central banks, this relationship has traditionally been modelled according to the *neoclassical investment theory* (Boivin et al., 2010). Pioneered by Jorgenson (1963) the theory links firms' capital demand with interest rates via the firms' user cost of capital.

[4] Models that incorporate the neoclassical link between interest rates, the user cost of capital and business investment include the Federal Reserve Board's MIT-Penn-SSRC model (Brayton et al., 1997), the ECB's Area-Wide Model, the Bank of England Quarterly Model (Harrison et al., 2005) and the Bank of Canada's Quarterly Projection Model (Coletti et al., 1996).

2.2.2 Neoclassical Investment Theory

The idea of a negative interest rate elasticity of investment had already been a standard feature in the dogma of classical economists (e.g. Smith, 1776; Ricardo, 1817). The first microeconomic foundation for this concept was laid down by early neoclassical economists, such as Alfred Marshall, who argued that investment is pushed to the point where the marginal utility of investment equals the rate of interest (Marshall, 1920).[5] Later, this concept formed the basis of modern capital and investment theories (e.g. Fisher, 1930; Keynes, 1936).

In the neoclassical theory of investment, Dale Jorgenson extended the approach of his predecessors beyond interest rates to include taxes, depreciation rates and capital gains in the analysis. These extra dimensions introduced the concept of *user costs of capital* in connection with investment decisions (Jorgenson, 1963). The starting point of the neoclassical investment theory is the assumption that a firm's demand for capital is determined by its objective to maximize its net worth.[6] A firm's optimal capital stock is reached when the marginal product of capital $f_K^{'}$ is equal to the rental price of one unit of capital service, which is the so-called user cost of capital UCC:

$$f_K^{'} = \frac{p^I}{p} \frac{(1 - k - \tau Z)}{(1 - \tau)} \left(\delta + r - \frac{\dot{p^I}}{p^I} \right) = UCC \tag{2.1}$$

where p denotes the output price, p^I the price of investment goods, k the rate of investment tax credit on new capital purchases, Z the present value of depreciation allowances, τ the corporate tax rate, δ the depreciation rate and r the real interest rate.[7] According to Jorgenson (1963), the rate of investment is determined by the firm's adjustment to the optimal capital stock.

In line with equation (2.1), according to the neoclassical investment theory interest rates do not affect business investment directly, but are embedded in the firms' user cost of capital, which in turn is linked to the investment decision. The successful

[5] 'When they have this amount, the marginal utility of the machinery [...] is measured by 4 percent. A rise in the rate of interest would diminish their use of machinery; for they would avoid the use of all that did not give a net annual surplus of more than 4 percent on its value. And a fall in the rate of interest would lead them to demand the aid of more capital, and to introduce machinery which gave a net annual surplus of something less than 4 percent on its value' (Marshall, 1920, p.299).

[6] Despite the neoclassical theory of factor demand being well known at that time, the profit maximizing consideration had been almost entirely ignored in the early empirical literature on business investment (Gould and Waud, 1973).

[7] See Appendix A.1 for a derivation of equation (2.1).

transmission of monetary policy impulses to business investment hinges on the significance and size of firms' user cost elasticity of capital.[8] Empirical studies that have examined the workings of the interest channel in Germany during the pre-crisis period have found a statistically significant effect of the user cost of capital on business investment (Table 2.1). The user cost of capital elasticity estimates range between -0.12 (Büttner et al., 2015) and -1.16 (Dwenger, 2014) depending on the dataset and estimation model employed.

Table 2.1: Studies on the Interest Rate Channel in Germany

Paper	Data	UCC Elasticity estimates
Mojon et al. (2001)	Semi-aggregated (1988-1997)	Between -0.68 and -0.15
von Kalckreuth (2001)	Firm level data (1988-1997)	Between -0.66 and -0.38
Harhoff and Ramb (2001)	Firm-level data (1987-1997)	Between -0.63 and -0.42
Büttner and Hönig (2011)	Firm-level data (1994-2007)	Between -1.16 and -1.03
Dwenger (2014)	Firm-level data (1987-2007)	Between -1.18 and -0.48
Dwenger and Walch (2014)	Firm-level data (1995-2004)	Between -0.52 and -0.43
Büttner et al. (2015)	Firm-level data (1994-2012)	Between -0.47 and -0.12

Jorgenson's neoclassical investment theory has substantially influenced the empirical literature on investment demand. By taking into account depreciation, interest rates and taxes, the theory suggests that both fiscal and monetary policy can influence business investment. This logic renders the theory highly appealing to policy makers, who have called for low interest rates and tax incentives – such as investment tax credit or accelerated depreciation – to stimulate investment. Though it is not free from criticism[9] and alternative investment theories have emerged, the neoclassical investment theory has remained a key framework for analysing investment demand. It has been widely employed in macro-econometric models at central banks (Boivin et al., 2010).

[8] The user cost elasticity of capital measures the percentage change of capital given a 1-percent change in the user cost of capital.

[9] Empirical evidence on the validity of the neoclassical investment theory is mixed. Early econometric studies based on aggregate time-series data did not definitively prove a statistically significant impact of the user cost of capital on investment. For an overview of studies, see Chirinko (1993) and Hassett and Hubbard (2002). Later empirical studies employing firm-level data were able to provide clearer evidence of a statistically significant effect of the user cost on investment, although not always of an economically relevant size (e.g. Cummins and Hassett, 1992; Cummins et al., 1994, 1996; Chirinko et al., 1999).

2.3 Interest Rates and Business Investment: Stylized Facts

The link between interest rates and investment, via firms' user cost of capital, is well established in the literature, as shown in the preceding section. Doubts about the proper functioning of this link have been raised, owing to weak investment activities in the post-crisis period despite record low interest rates. Using aggregate data we analyse to what extent business investment and interest rates in Germany have covaried during the past two decades.

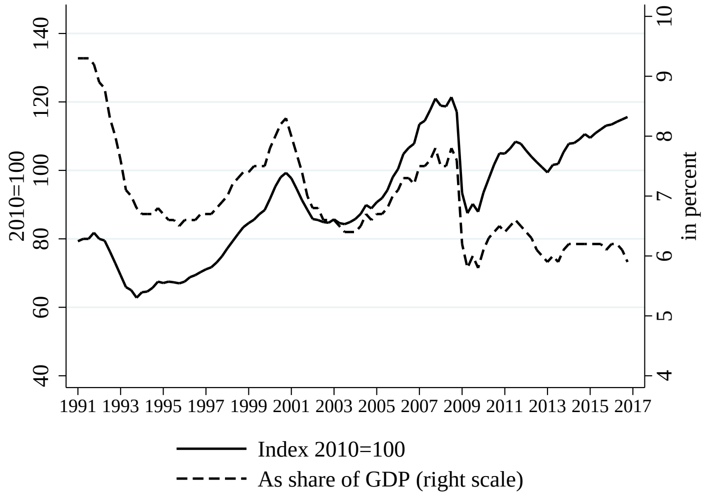
2.3.1 The Link Between Interest Rate and Investment in Germany

Business investment in Germany has fluctuated dramatically since the early 1990s (Figure 2.1). The reunification boom was followed by a sharp contraction in corporate investment activities. During the subsequent recovery between 1995 and 2000, business investment grew by almost 50 percent. The bursting of the dot-com bubble and ensuing economic stagnation in Germany caused contraction in business investment between 2001 and 2004; this was followed by another period of strong increase during the run-up to the financial crisis. Real business investment grew by more than 40 percent between 2003 and the end of 2007. With the outbreak of the financial crisis, the boom ended. Real business investment contracted by almost 30 percent between the end of 2007 and the end of 2009.

Although business investment recovered quickly after the financial crisis, increasing by 24 percent between mid-2009 and mid-2011, it has not changed much since then. Between mid-2011 and late 2016, real business investment increased by only 6.6 percent and remained below the pre-crisis level. Furthermore, business investment as a share of GDP is still rather low. It accounted for around 5.9 percent at the end of 2016, compared with more than 9 percent after the reunification, 8 percent at the turn of the millennium, and 7.8 percent at the end of 2007 (Figure 2.1).

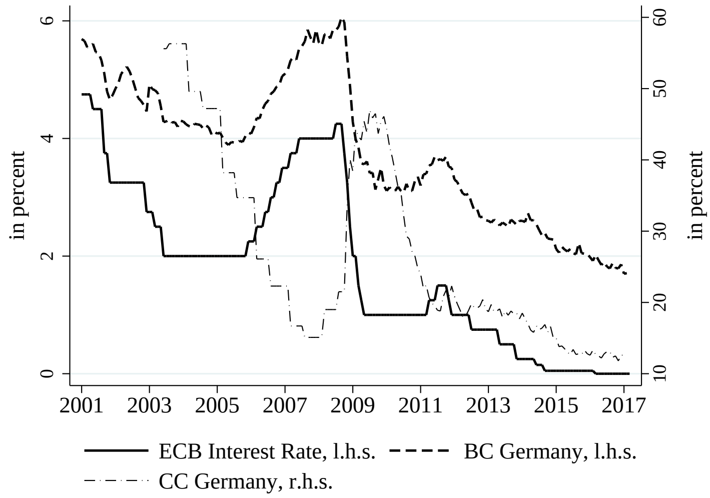
The post-crisis weakness in business investment is surprising. Owing to the ECB's expansionary monetary policy, the borrowing costs of non-financial corporations (NFCs) have substantially declined and firms' access to finance is excellent (Figure 2.2). This raises the question whether the traditional link between interest rates and investment still functions. Following Boivin et al. (2010), we evaluate the link by analysing the co-movement of the growth rates of real business investment, the ECB monetary policy rate and the borrowing cost for NFCs in Germany.

Figure 2.1: Real Business Investment in Germany



Source: Destatis, own calculations. Business investment defined as private sector equipment investment, which comprises investment in machinery and vehicles.

Figure 2.2: Borrowing Costs and Credit Constraints of German NFCs

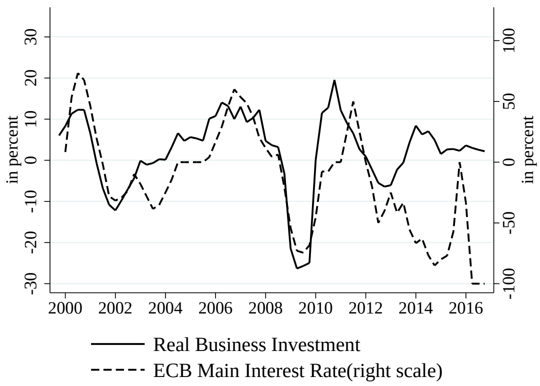


Source: ECB, Ifo. ECB Interest Rate - interest rate on the main refinancing operations. BC - borrowing costs for NFCs defined as the weighted average interest rate charged by banks to NFCs on new loans. CC (credit constraints) - share of manufacturing sector firms reporting restrictive lending by the banks.

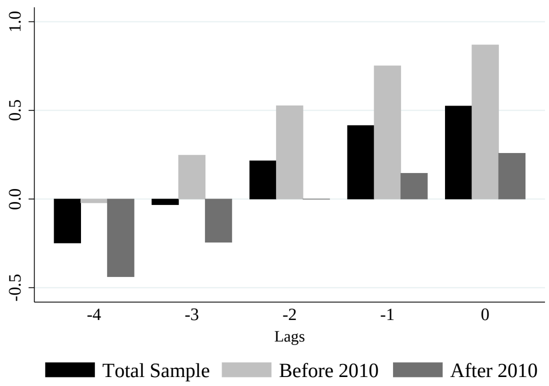
Figure 2.3a shows the year-over-year growth rate of real business investment in Germany, plotted against the growth rate of the ECB monetary policy rate. In Figure 2.3b we plot the correlation coefficients of the growth rate of real business investment and several lags of the growth rate of the monetary policy rate. According to the interest rate channel theory, the correlation should be negative. This would mean a decline in the policy rate should be followed by an increase in business investment. However, the rather strong co-movement of the two series, shown in Figure 2.3a – particularly until 2011 – suggests a positive interrelationship. The positive correlation coefficients between the growth in business investment and lagged changes in the monetary policy rate in the sample period from 2000Q1 to 2009Q4 support this notion. Boivin et al. (2010) argue that the positive relationship reflects policy makers' focus on inflation stability and the tendency to lean against strengthening (or weakening) in demand. In the period 2010Q1 to 2016Q4, however, correlations have become negative, indicating that a reduction in the monetary policy rate was followed by an increase in business investment within three to four quarters. However, the post-crisis sample is rather small and the null-hypothesis that the correlation is statistically significant from zero cannot be rejected.

Figure 2.3: Real Business Investment and ECB Key Interest Rate

(a) YoY Growth Rates



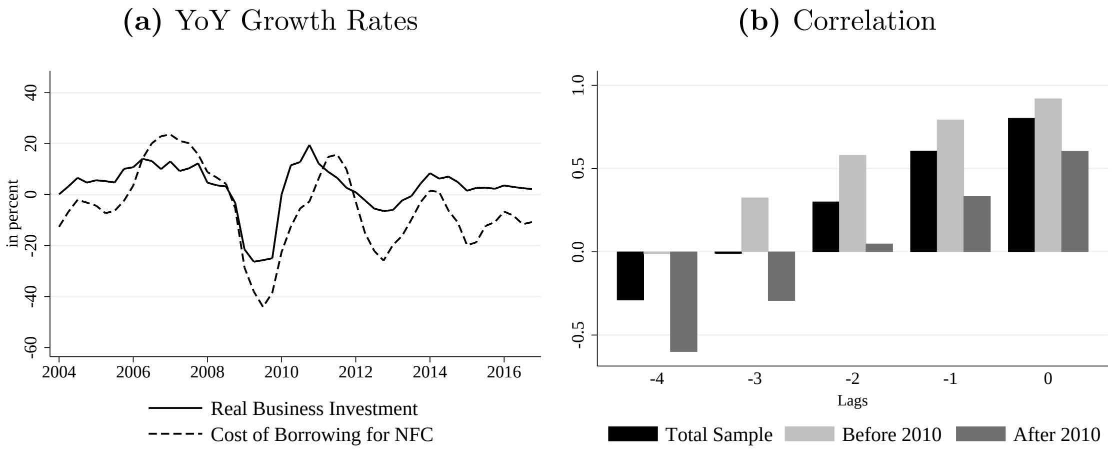
(b) Correlation



Source: Destatis, ECB, own calculations. Correlation between the growth rate of real business investment and the lagged growth rate of the ECB interest rate on main refinancing operations. Total Sample: 2000q1-2016q4; Before 2010:2000q1-2009q4; After 2010: 2010q1-2016q4.

Analogous evidence can be found for the relationship between the growth rates of real business investment and borrowing costs for NFCs, as shown in Figure 2.4a and Figure 2.4b. Because bank loans are one of the most important sources of external finance for most corporations, particularly SMEs, borrowing costs should be an important driver of firms' user cost of capital (EIB, 2015). Similar to the monetary policy rate, changes in real business investment seem to closely follow changes in NFC borrowing costs – indicating a positive interrelationship (Figure 2.4a). The correlation between the lags of borrowing costs changes and business investment changes was positive for the period 2004Q1 to 2009Q4. Thereafter it shifted to the negative, without being statistically significant (Figure 2.4b.).

Figure 2.4: Real Business Investment and Borrowing Costs of NFCs



Source: Destatis, ECB, own calculations. Correlation between the growth rate of real business investment and the lagged growth rate of borrowing costs for NFCs. Total Sample: 1999q1-2016q4; Before 2010:1999q1-2009q4; After 2010: 2010q1-2016q4.

Overall, aggregate data do not offer strong support for a negative investment–interest rate relationship such as that proposed by the interest rate channel and neoclassical investment theory – neither during the pre-crisis period nor during the post-crisis period. However, the existence of a neoclassical link between interest rates and investment should not yet be rejected. Chirinko et al. (1999) point out that the results of studies based on aggregate data may be biased due to simultaneity problems, capital market frictions as well as firm heterogeneity.

2.3.2 Expectations and Business Investment

The post-crisis business investment development in Germany has been the focus of numerous studies, which analysed the potential causes of the weakness (e.g. Schwartz and Gerstenberger, 2014, 2015; Alm and Meurers, 2015). Some of these studies have identified uncertain and gloomy business expectations as the main cause of firms' reluctance to invest (e.g. Gerstenberger and Schwartz, 2014; Schwartz, 2015; Heymann and Schneider, 2017).

The data show that business expectations of the German corporate sector have indeed been rather volatile in the post-crisis period. According to the ifo Business Expectations Index shown in Figure 2.5, firms' business outlook reached an all-time low in early 2009 but quickly recovered in 2010. However, the intensification of the sovereign debt crisis in 2012 severely lowered business expectations in Germany. After a modest recovery in 2013, firms' business outlook remained at a level that was lower than in 2006 and 2007.

Research has shown that medium- to long-term business expectations are important drivers of investment. The irreversibility of investment decisions and the durability of capital goods make it necessary for firms to incorporate not only current demand conditions in their investment decisions but also expectations of future demand (Eckstein, 1965). Keynes (1936) emphasized the role of entrepreneurs' 'state of confidence' as significantly affecting investment decisions.[10] Using micro-data from a survey among Chief Financial Officers, Gennaioli et al. (2016) provide empirical evidence that expectations about earnings growth are important predictors of planned and actual investment.

Figure 2.5: Business Expectations of the German Corporate Sector

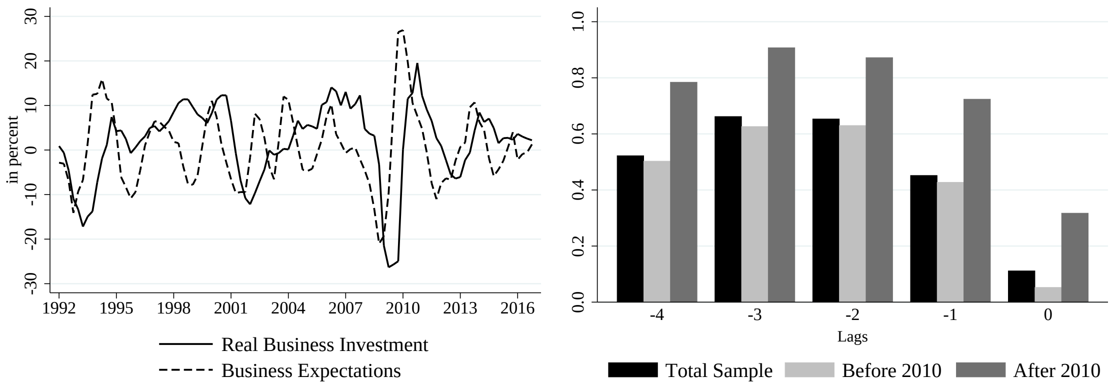
Source: Ifo Business Expectations Index (2005=100). Higher values indicate positive expectations.

The likely importance of business expectations for investment decisions is supported by an analysis of aggregate data. Figure 2.6a shows a strong co-movement between German firms' business expectations and real business investment, with changes in expectations leading investment changes. There is a strong and statistically significant positive correlation between changes in real investment and the various lags of business expectation changes (Figure 2.6b). Furthermore, the correlation strengthened notably after 2010Q1. Hence, expectations seem to have become even more important after the crisis.

[10] Keynes (1936) argued that '[...] economic prosperity is excessively dependent on a political and social atmosphere which is congenial to the average business man', and that '[...]in estimating the prospects of investment, we must have regard, therefore, to the nerves and hysteria and even the digestions and reactions to the weather of those upon whose spontaneous activity it largely depends' (p.103)

Figure 2.6: Real Business Investment and Business Expectations

(a) YoY Growth Rates **(b)** Correlation



Source: Destatis, Ifo, own calculations. Correlation between the growth rate of real business investment and the lagged changes of business expectations (ifo Business Expectations Index). Total Sample: 1999q1-2016q4; Before 2010:1999q1-2009q4; After 2010: 2010q1-2016q4.

2.4 Empirical Analysis

Based on aggregate data, we cannot identify the negative link between interest rates and investment that is predicted by the interest rate channel and neoclassical investment theory. Pessimistic business expectations might have played a role in depressing post-crisis investment dynamics. We proceed our analysis with firm-level data and test the proposed neoclassical link between business investment and the user cost of capital, as described in Section 2.2.

2.4.1 Estimation Strategy

The aim of our empirical analysis is to estimate the user cost elasticity of capital among German SMEs in the post-crisis period. Furthermore, we evaluate how expectations of future business conditions affected the firms' responsiveness to user cost changes. The starting point for our empirical model is a capital demand equation, derived from a neoclassical model of a profit-maximizing firm. Following Eisner and Nadiri (1968) we assume a CES-production function with a constant elasticity of substitution between capital and labour:

$$F(L_{i,t}, K_{i,t}) \equiv S_{i,t} = A_t[\alpha_i K_{i,t}^{-\rho} + (1-\alpha_i)L_{i,t}^{-\rho}]^{-v/\rho} \tag{2.2}$$

with: $S_{i,t}$ = output defined as net sales
$K_{i,t}$ = capital input
$L_{i,t}$ = labour input
A_t = year specific production technology (productivity)
v = elasticity of scale
ρ = $(1/\sigma) - 1$ determines the elasticity of substitution
σ = elasticity of substitution between capital and labour
α_i = capital share

The optimal capital stock K^* is derived from the first order condition of a profit maximizing firm. That is, the marginal productivity of capital is equal to its marginal cost (i.e. the user cost of capital):[11]

$$K^*_{i,t} = H_{i,t} S^{\beta}_{it} UCC^{-\sigma}_{it} \tag{2.3}$$

with: $H_{i,t} = D_i T_t = (\alpha_i v)^{\sigma} A_t^{[\frac{\sigma-1}{v}]}$
$\beta = \sigma + \frac{1-\sigma}{v}$

Equation (2.3) shows that the optimal capital stock of a firm depends on the firm's level of output (sales) $S_{i,t}$, the firm's user cost of capital $UCC_{i,t}$, a firm-specific distribution parameter D_i[12] and a productivity parameter T_t (in equation 2.3 reflected by $H_{i,t}$). Taking the log of both sides, we obtain the following linear equation:

$$k_{i,t} = h_{i,t} + \beta s_{i,t} - \sigma ucc_{i,t} \tag{2.4}$$

where $k_{i,t}$ denotes the log of the optimal capital stock, $s_{i,t}$ the log of sales, $ucc_{i,t}$ the log of the user cost of capital and $h_{i,t}$ the log of $H_{i,t}$.[13]

Differencing equation (2.4) and approximating the net growth in capital stock, $\Delta k_{i,t}$, using the formula $I_{i,t}/K_{i,t-1} - \delta_i$, with $I_{i,t}$ and δ_i denoting investment and depreciation, respectively, we obtain the following model:

$$\frac{I_{i,t}}{K_{i,t-1}} = \beta \Delta s_{i,t} - \sigma \Delta ucc_{i,t} + u_{i,t} \tag{2.5}$$

[11] See Appendix A.2 for a detailed derivation of equation (2.3).
[12] D_i captures the firm's relative factor shares of capital and labour.
[13] Assuming a Cobb-Douglas production function with $\sigma = 1$ and constant returns to scale ($v = 1$) equation (2.4) reduces to $k_{i,t} = \log \alpha_i + s_{i,t} - ucc_{i,t}$.

with: $u_{i,t} = \eta_i + \lambda_t + \epsilon_{i,t}$

The change of $h_{i,t}$ is captured by including time-specific shocks, λ_t, a firm-specific constant, η_i (reflecting depreciation δ_i and possible trends in the capital demand equation 2.4) and idiosyncratic transitory shocks, $\epsilon_{i,t}$ (von Kalckreuth, 2001; Chatelain et al., 2001). Equation (2.5) links the percentage change in capital stock ($\Delta k_{i,t}$) – approximated by the 'investment rate' $I_{i,t}/K_{i,t-1}$ – to percentage changes in sales and the user cost of capital.

To account for the fact that adjustment to the desired capital stock is not instant,[14] we follow the empirical literature and assume an econometric adjustment process in the form of an autoregressive-distributed lag (ADL) model (e.g. Harhoff and Ramb, 2001; von Kalckreuth, 2001; Bond et al., 2003). We derive our baseline model:

$$\frac{I_{it}}{K_{i,t-1}} = \sum_{l=0}^{L} \lambda_l \frac{I_{i,t-l}}{K_{i,t-l-1}} + \sum_{m=0}^{M} \beta_m \Delta s_{i,t-m} - \sum_{n=0}^{N} \sigma_n \Delta ucc_{i,t-n} + u_{i,t} \tag{2.6}$$

where L, M and N denote the maximum included lags of the explanatory variables.[15] From equation (2.6) we can derive the short-run and long-run effect of a one-period change in Δucc_t. The short-run effect corresponds to:

$$\frac{d\Delta k_t}{d\Delta ucc_t} = \sigma_0, \tag{2.7}$$

whereas the long-run effect is the sum of the effects of shocks in each period. It is given by:

$$\frac{\sum_{h=0}^{N} \sigma_h}{1 - \sum_{h=1}^{L} \lambda_h} = \eta_{ucc} \tag{2.8}$$

The long-run user cost elasticity of capital, η_{ucc}, captures the long-run percentage change in the capital stock K as a reaction to a one-percent change in the *level* of the user cost of capital (due to a one-period increase in the growth rate of the user cost of capital) (see e.g. von Kalckreuth, 2001). The analogous definition applies to the short-run and long-run effects of a one-period change in Δs_t.[16]

[14] Frictions prohibiting the instantaneous adjustment of the capital stock include, inter alia, adjustment costs, delivery lags, irreversibility constraints and time-to-build lags (von Kalckreuth, 2001).

[15] Economic theory does not provide information about the optimal lag-structure, so it must be determined empirically. We determine the optimal number of lags in the estimation model by testing various specifications and comparing the test statistics described below.

[16] The long-run sales elasticity of capital is given by $\eta_s = (\sum_{h=0}^{M} \beta_h)/(1 - \sum_{h=1}^{L} \lambda_h)$.

We estimate equation (2.6) using data from the post-crisis period, as described below. We compare the estimates of the long-run user cost elasticity of capital with pre-crisis findings reported in earlier studies. The aim is to evaluate whether firms have been responsive to user cost changes (i.e. interest rate changes) in the period after the financial crisis, during which the ECB's monetary policy measures have led to a significant decline in interest rates.

In addition to the re-estimation of the user cost elasticity of capital for the post-crisis period, we are interested in the effect of business expectations on firms' investment decisions. To test the effect of business expectations, we proceed in two steps. First we include a firm-specific categorical variable $BE_{i,t}$, which captures whether the firm had positive, neutral or negative business expectations (e.g. Büttner and Hönig, 2011). We expect firms with neutral or negative business expectations to display a lower investment rate than firms with positive expectations. We estimate the following model:

$$\frac{I_{it}}{K_{i,t-1}} = \sum_{l=0}^{L} \lambda_l \frac{I_{i,t-l}}{K_{i,t-l-1}} + \sum_{m=0}^{M} \beta_m \Delta s_{i,t-m} - \sum_{n=0}^{N} \sigma_n \Delta ucc_{i,t-n} + \alpha BE_{i,t} + u_{i,t} \quad (2.9)$$

Second, to assess whether firms with different business expectations reacted differently to user cost changes, we estimate equation (2.6) for subgroups of firms that differ in business expectations. We expect that firms with neutral or negative expectations would react less strongly to user cost changes, and hence would display a lower user cost elasticity of capital than firms which had positive expectations.

The econometric specifications in equation (2.6) and (2.9) might suffer from several shortcomings, which could lead to inconsistent coefficient estimates if standard panel data models are applied. First, the lagged dependent variable $I_{i,t-l}/K_{i,t-l-1}$ is positively correlated with the error term $u_{i,t}$ due to the presence of individual fixed-effects η_i.[17] Second, research has shown that simultaneity between interest rates and investment shocks distorts the user cost elasticity towards zero and that firm

[17] Hence, estimating equations (2.6) and (2.9) using ordinary least squares (OLS) would give inconsistent estimates. The positive correlation between the lagged dependent variable and the error term leads to a upward bias of its estimated coefficients λ_l. Since λ_l enters equation (2.8) as denominator, the UCC elasticity η_{ucc} would be biased downwards. To solve this endogeneity problem one can transform the data and remove the fixed effects η_i for instance by applying the fixed effects (within) estimator (FE). However, Nickell (1981) shows that the transformed lagged dependent variable and the transformed error term are still (negatively) correlated resulting in an underestimation of the true coefficients λ_l and thus an overestimation of η_{ucc}. A consistent estimator of λ_l would lie within or near the boundaries of the OLS and FE estimates (Bond, 2002).

investment shocks could also be contemporaneously correlated with sales (Chirinko et al., 1999).

We therefore estimate equations (2.6) and (2.9) using a General Method of Moments (GMM) estimator, which allows one to deal with the dynamic structure of the model as well as with predetermined or endogenous explanatory variables. More specifically, we employ the two-step System-GMM as outlined by Arellano and Bover (1995) and Blundell and Bond (1998), with heteroskedasticity-robust standard errors and a Windmeijer (2005) finite-sample correction. The System-GMM estimator is consistent only in the absence of higher-order serial correlation of the error-term $\epsilon_{i,t}$. To test the validity of this condition, we use the Arellano–Bond test (Arellano and Bond, 1991). Whereas the AR(1) autocorrelation statistic should be significant, the AR(2) statistic should be such that the null hypothesis (no autocorrelation) cannot be rejected. Furthermore, we test for overidentifying restrictions using the Sargan test.

2.4.2 Data and Variable Definition

The basis of our empirical analysis is the *KfW Mittelstandspanel*, an annual survey covering German micro-, small and medium-sized enterprises having less than EUR 500 million annual turnover. The database comprises qualitative and quantitative data from 60,653 firms over a 14-year period (2002–2015). We extend previous research by including in our analysis firms that were not subject to publication requirements and whose data were therefore not captured by other widely-used sources of accounting data at the firm level (e.g. Hoppenstedt database). Furthermore, our study is the first to include data beyond the year 2012 (Büttner et al., 2015); hence, our analysis covers a longer timespan of the post-crisis period than previous work.

To control for outliers, we discard firm-year observations that belong to the 1^{st} or 99^{th} percentile of the variables of interest, which are the investment-capital ratio, the user cost of capital and real sales (e.g. von Kalckreuth, 2001; Dwenger, 2014). Furthermore, we restrict the sample to include only firms that have participated in the survey over four consecutive years or more.[18] Taking into account missing observations, the final sample contains 8,970 observations for 1,277 SMEs for the

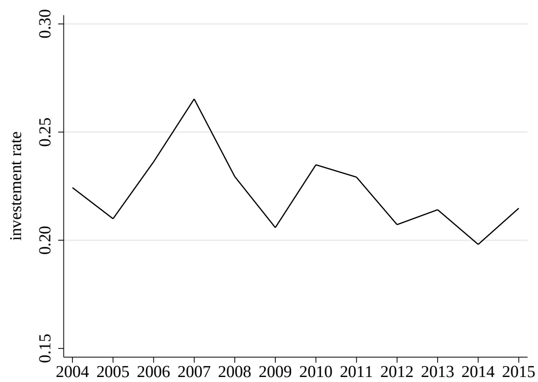
[18] Since we analyse changes in the explanatory variables, and include at least two lags in the analysis, a firm is required to appear in the dataset in the three preceding years.

period 2004–2015.[19] The sample is unbalanced owing to missing data and differing participation behaviour among the firms. Appendix A.3 provides an overview of the sample structure.

Dependent Variable

The dataset includes information on the amount invested in year t (depicted $I_{i,t}$).[20] This value is divided by the capital stock value of the preceding year ($K_{i,t-1}$) – that is, tangible assets – to derive the dependent variable, the investment–capital ratio $I_{i,t}/K_{i,t-1}$, which captures the growth in capital stock.

Figure 2.7: Annual Average Investment Rate



Source: KfW, own calculations.

Figure 2.7 shows the resultant average yearly investment rate among our sample. The investment rate of German SMEs increased significantly between 2005 and 2007, reflecting the pre-crisis investment boom. After the sharp decline in 2008/2009 and the recovery in 2010, investment rates slowly declined. The trends for the investment rate among the studied firms resembles the aggregate data as discussed in Section 2.3.1. Summary statistics of the dependent and independent variables are shown in Table 2.2.

Explanatory Variables

The variable sales ($S_{i,t}$) is measured as turnover, deflated using an industry-specific output-price deflator. German SMEs experienced strong growth in real sales prior

[19] Our sample covers fewer years than the original sample, owing to some variables not being available for all survey years.

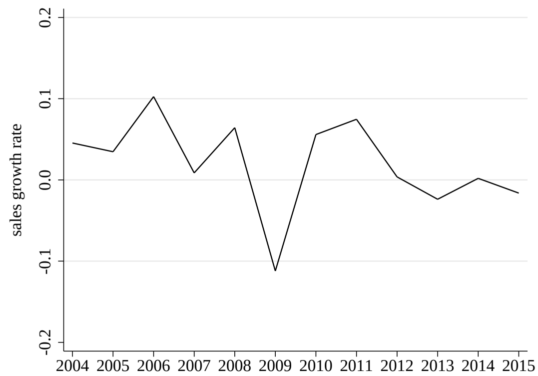
[20] Our study differs from previous studies that define investment as additions to plant, property and equipment, taken from the *Anlagespiegel*, less disposals from fixed tangible assets (e.g. Dwenger, 2014). In those studies, capital stock K is calculated by applying a perpetual inventory method.

Table 2.2: Descriptive Statistics

	Mean	SD	Min	Max
$I_{i,t}/K_{i,t-1}$	0.224	0.282	0.000	1.500
$UCC_{i,t}$	0.083	0.022	0.018	0.138
$\Delta ucc_{i,t}$	-0.050	0.163	-1.864	0.828
$S_{i,t}$ (in 1000 EUR)	13,731	21,692	106	213,857
$\Delta s_{i,t}$	0.021	0.299	-4.344	6.977

to the crisis, with an average annual increase of 5.1 percent between 2004 and 2008 (Figure 2.8). Real sales dropped dramatically in 2009 by 11.2 percent, but quickly recovered in 2010 (by 5.6 percent) and 2011 (7.5 percent). As of 2012, real sales growth was rather low or even negative, with an average annual growth rate of around -1 percent between 2012 and 2015.

Figure 2.8: Annual Average Real Sales Growth



Source: KfW, own calculations.

The construction of the firm-specific user cost of capital variable is based on Jorgenson (1963) and Jorgenson and Hall (1967). Following Auerbach (1983) and Hayashi (2000), we employ a weighted-average definition of the user cost of capital:[21]

$$UCC_{i,t} = \frac{P_t^I}{P_{j,t}} \frac{1 - A_{j,t}}{1 - \tau_t} \left(WACC_{i,t} + d_{j,t} - (1 - d_{j,t}) \frac{\Delta P_{t+1}^I}{P_t^I} \right) \tag{2.10}$$

where $UCC_{i,t}$ represents the user cost of capital for firm i at time t, P_t^I is the price level of investment goods, and $P_{j,t}$ is the industry-specific output price index. The term $A_{j,t}$ is the industry-specific discounted value of depreciation allowances, τ_t is

[21] This is in contrast to other studies that use German firm-level data, such as Harhoff and Ramb (2001), von Kalckreuth (2001) and Dwenger (2014) which use the King and Fullerton (1984) approach.

the corporate tax rate, $WACC_{i,t}$ is the weighted average cost of capital, $d_{j,t}$ is the industry-specific depreciation rate, and the ratio $\Delta P^I_{t+1}/P^I_t$ is a forward-looking inflation component for investment goods. Appendix A.4 provides details of the data used in the construction of the user cost of capital variable.

The firm-specific weighted average cost of capital $WACC_{i,t}$ takes into account the financial structure of firm i, by weighting the costs of debt and equity with their respective shares in total funds (e.g Mojon et al., 2001; Luennemann and Mathae, 2001; Chatelain et al., 2001):

$$WACC_{i,t} = \frac{D_{i,t}}{D_{i,t} + E_{i,t}} * ar_{i,t} * (1 - \tau_t) + \frac{E_{i,t}}{D_{i,t} + E_{i,t}} * er_t \tag{2.11}$$

where $D_{i,t}$ denotes gross debt, $E_{i,t}$ denoted equity, and $ar_{i,t}$ refers to the apparent interest rate. The term er_t is the equity rate approximated by the long-term interest rate.[22] The apparent interest rate is measured as interest expenses over gross debt:

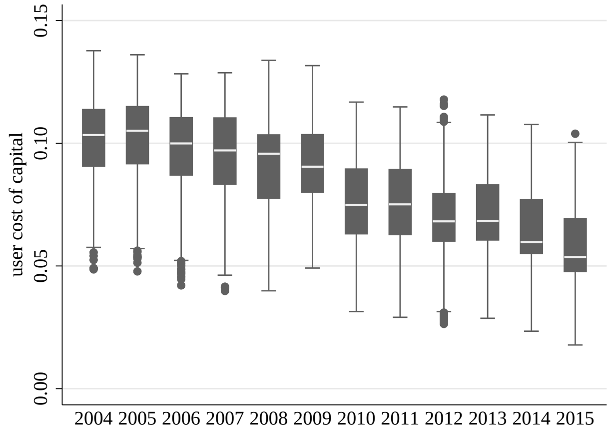
$$\text{with } ar_{i,t} = \frac{interest\ expenses_{i,t}}{D_{i,t}} \tag{2.12}$$

Figure 2.9 shows that SMEs' user cost of capital declined substantially during the observation period. The average user cost of capital among the sample firms was around 10.2 percent in 2004, but by 2015 it had dropped to 5.7 percent. To evaluate which factors had caused the decline in SMEs' user cost of capital during the observation period, we re-estimate various user cost specifications. We hold various components constant in turn, as follows: the tax rate (UCC_TAX), prices (UCC_PRICE), the capital structure (UCC_CSTRUC), and interest rates – both the equity rate and the apparent interest rate (UCC_INTR). The results are shown in Figure 2.10.

Figure 2.10a illustrates the development of the various user cost specifications. Figure 2.10b shows the respective differences between the user cost specifications and the baseline user cost specification (UCC). The results suggest that changes in tax rates, capital structure and prices accounted for minimal changes in SMEs' user cost of capital during the observation period. The respective differences between UCC_TAX, UCC_CSTRUC and UCC_PRICE relative to the baseline specification are small. The largest changes in the user cost of capital were associated with interest rate

[22] Following for instance Chatelain and Tiomo (2001) and Chatelain et al. (2001), we use the German 10-year government bond yield.

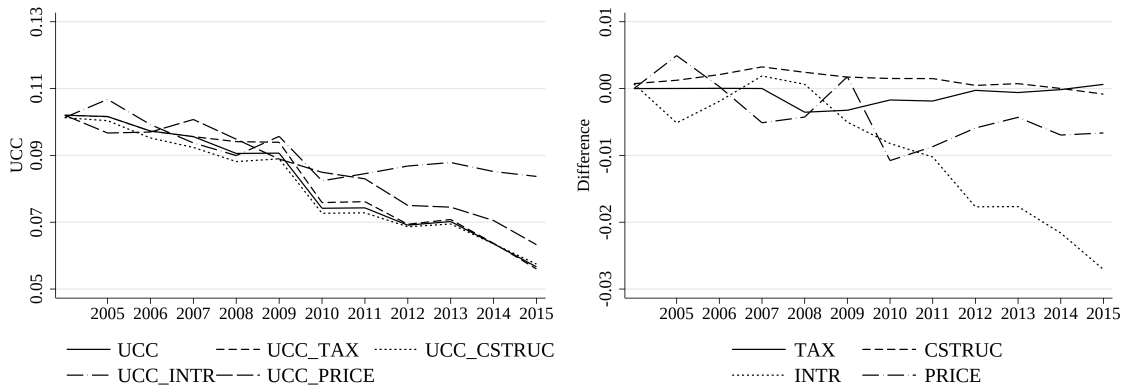
Figure 2.9: Annual Average User Cost of Capital



Source: KfW, own calculations.

Figure 2.10: User Cost of Capital Specifications

(a) Components **(b)** Difference



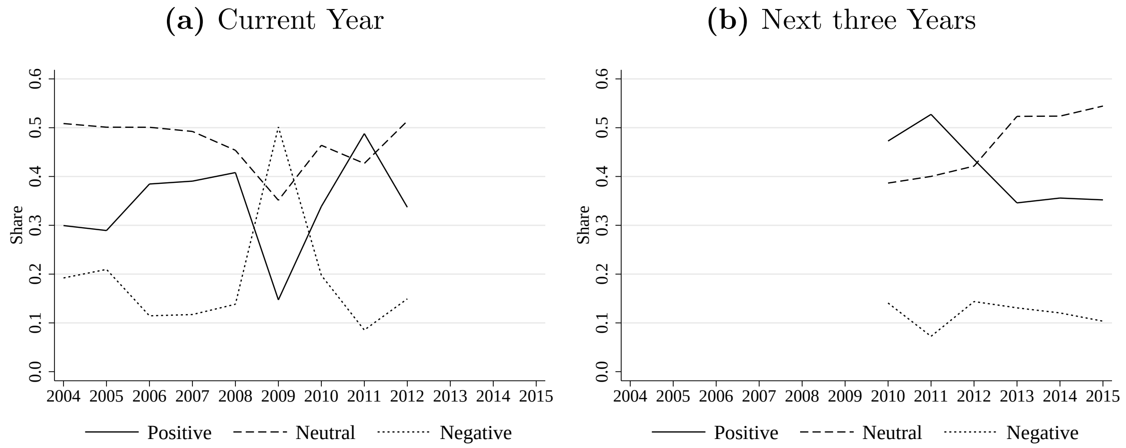
Notes: UCC: user cost calculated following equation (2.10). UCC_TAX: holding the tax rate constant at the rate in 2004. UCC_CSTRUC: holding the capital structure constant at the sample mean in 2004. UCC_INTR: holding the equity rate constant at the rate in 2004, and the apparent interest rate constant at the sample mean in 2004. UCC_PRICE: holding output and investment goods prices constant at the rate in 2004. TAX: difference between UCC and UCC_TAX; equivalent for CSTRUC, INTR and PRICE.

changes, as illustrated by the plot for the variable UCC_INTR. If interest rates had remained at the 2004 level, SMEs' user cost of capital would have been around 2.7 percentage points higher in 2015 than they actually were.

Business Expectations

As explained in the previous section, we include business expectations in our empirical analysis. This information is included as the categorical variable $BE_{i,t}$, and by splitting the sample according to firms' business expectations. For the years 2004 to 2011, our dataset includes information on one-year sales expectations, reflecting short-term business expectations.[23] As of 2010, the dataset also includes three-year sales expectations, reflecting medium-term business expectations. As business investments are generally of a long-term character, we regard medium or long-term business expectations as being particularly relevant to investment decisions. As our medium-term business expectation indicator does not cover the entire sample period but is available only from 2010 onwards, we approximate the data for 2008 and 2009[24] based on the one-year sales expectations.[25]

Figure 2.11: Sales Expectations



Notes: Firms were asked how they expect their sales to develop in the current year/in the next three years. Positive - sales will increase. Neutral - sales will remain constant. Negative - sales will decline.

As shown in Figure 2.11a, during the years preceding the financial crisis, our sample firms' business expectations were rather optimistic. In 2008, around 40 percent of the SMEs in the sample expected their sales to increase. Only 13.5 percent expected their sales to decline. In the crisis year, 2009, business expectations plummeted dramatically. Around 50 percent of the firms expected their sales to decline, and only 15 percent expected sales to increase. Owing to the fast economic recovery, the firms' business outlook quickly recovered, too. In 2011, almost 50 percent of the firms expected sales increases during that year, and 53 percent expected sales increases over the next three years (Figure 2.11b). However, after 2011, firms' medium-term business

[23] The participating firms were asked to state whether they expected their sales to (i) increase, (ii) remain constant or (iii) decline in the current year.

[24] The estimation period covers the years 2008 to 2015, and differs from the sample period (2004–2015) due to the inclusion of several lags as instrumental variables in our estimation equation. As BE is not instrumented, only the data from 2008 onwards is necessary.

[25] Because we have access to data on both the one-year and the three-year sales expectations for the period 2010 to 2012, we can compare their values. We find that for 72 percent of all observations, both indicators are identical. This finding implies that short-term expectations are relatively good approximates for medium-term business expectations.

outlook became less optimistic. The number of firms expecting sales increases in the following three years declined to around 35 percent in 2015. Around 65 percent of the firms expected no sales increases or even a decline.

Descriptive statistics suggest SMEs' investment rates differ according to their business expectations. As shown in Table 2.3, the average investment rate of firms with positive three-year sales expectations is almost 26 percent. Firms with negative expectations display a much lower investment rate (19.5 percent).

Table 2.3: Investment Rate and Business Expectations

Sample Mean	Positive Exp.	Neutral Exp.	Negative Exp.
22.1	25.8	20.1	19.5

Notes: Positive - sales are expected to increase in the next three years. Neutral - sales are expected to remain constant. Negative - sales are expected to decline.

2.4.3 Estimation Results

Table 2.4 shows the estimation results of the ADL-model specified in equation (2.6). After testing several specifications with various lag-structures, we include in our preferred model two lags of the dependent variable $I_{i,t}/K_{i,t-1}$, the contemporary value and two lags of $\Delta s_{i,t}$, and the contemporary value and three lags of $\Delta ucc_{i,t}$.[26] We also include a constant, as well as year dummies to control for macroeconomic influences on firm investment. Table 2.4 shows the complete list of coefficients of the included variables, the sum of the lagged dependent variable ($\sum I_{i,t-l}/K_{i,t-l-1}$), and the estimated long-run elasticities of sales and the user cost of capital (η_s and η_{ucc}).

As a starting point we estimate equation (2.6) using OLS and the fixed-effects (FE) estimator. The results are shown in columns (1) an (2) of Table 2.4. For both estimation methods, the coefficients of the lags of the dependent variable are statistically significant at the 1-percent level. However, they differ in sign. In the OLS estimation the coefficients are positive but in the FE estimation they are negative. The difference is due to the OLS estimates being biased upward and the FE estimates

[26] Using System-GMM we ran several specifications of models (2.6) and (2.9), for the total sample and subsamples, using various lag-lengths and instruments. We evaluated each specification based on the Arellano-Bond and Sargan test statistics. We chose the specification that gave consistent results for all models (2.6 and 2.9) and subsamples using the same set of instruments (see e.g. von Kalckreuth, 2001). Our lag-length choice is consistent with previous studies that used ADL models (Chatelain et al., 2001; von Kalckreuth, 2001).

being biased downward, owing to autocorrelation. For both models the sum of the autoregressive coefficients is within the unit interval, which is consistent with model stability (Debarsy et al., 2012).[27]

Table 2.4: Results - Baseline Model

$I_{i,t}/K_{i,t-1}$	(1) OLS	(2) FE	(3) GMM
$I_{i,t-1}/K_{i,t-2}$	0.2800***	-0.1665***	0.1102
	[0.0247]	[0.0336]	[0.1171]
$I_{i,t-2}/K_{i,t-3}$	0.1668***	-0.1547***	0.0657**
	[0.0199]	[0.0229]	[0.0295]
$\sum I_{i,t-l}/K_{i,t-l-1}$	0.4468***	-0.3212***	0.1759
	[0.0258]	[0.0425]	[0.1164]
$\Delta s_{i,t}$	0.0961***	0.0835***	0.0145
	[0.0207]	[0.0295]	[0.0579]
$\Delta s_{i,t-1}$	0.0936***	0.1130***	0.0355
	[0.0171]	[0.0293]	[0.0339]
$\Delta s_{i,t-2}$	0.0285*	0.0643**	0.0065
	[0.0163]	[0.0258]	[0.0211]
η_s	0.3944***	0.1974***	0.0686
	[0.0818]	[0.0588]	[0.1177]
$\Delta ucc_{i,t}$	-0.0984***	-0.0663	-0.2048
	[0.0368]	[0.0433]	[0.1332]
$\Delta ucc_{i,t-1}$	-0.1119***	-0.0582	-0.1554*
	[0.0388]	[0.0516]	[0.0828]
$\Delta ucc_{i,t-2}$	-0.0818**	-0.1253**	-0.1287*
	[0.0358]	[0.0543]	[0.0687]
$\Delta ucc_{i,t-3}$	-0.0056	-0.0632	-0.0620
	[0.0288]	[0.0384]	[0.0431]
η_{ucc}	-0.5382***	-0.2369**	-0.6685*
	[0.1706]	[0.1161]	[0.3821]
Observations	3,283	3,283	3,283
AR(1) (p-value)			0.0007
AR(2) (p-value)			0.7486
Sargan test (p-value)			0.3501

Notes: Dependent variable is $I_{i,t}/K_{i,t-1}$. Column (1) is estimated using OLS. Column (2) is estimated using the FE estimator. Column (3) is estimated using System-GMM. The lagged investment–capital ratio, sales and the user cost of capital are treated as endogenous and are instrumented. Instruments are the values (in levels) of $\Delta ucc_{i,t}$ and $\Delta sales_{i,t}$, lagged at least two periods and earlier when feasible, and the second lag of $I_{i,t}/K_{i,t-1}$. Year dummies and a constant are included. Standard errors in parentheses, $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

[27] Values outside the unit interval imply an unstable dynamic of the model, '[...] with accelerating divergence away from the equilibrium values' (Roodman, 2009a, p.103).

Furthermore, the point estimates (short-run coefficients)[28] of contemporary and lagged sales growth are statistically significant, which implies a positive relationship with a change in capital stock. Hence, a short-term increase in sales growth is associated with a short-term increase in capital. The long-run elasticity of sales varies between 0.2 and 0.39; these results are statistically significant at the 1-percent level in both estimation models.[29] The point estimates of the contemporary and lagged user cost of capital growth rate are negative, implying an inverse relationship with the growth in capital stock. However, not all lags are statistically significant in both models. The long-run user cost elasticity of investment is estimated based on equation (2.8) and varies between -0.54 and -0.24 depending on the estimation method. The null hypothesis, which stated that the long-run effect of user cost of capital would be equal to zero, is rejected for both estimations at the 1-percent level.

Because the coefficients of the OLS and FE models might be biased, we re-estimate the baseline model using System-GMM. The results are shown in column (3) of Table 2.4. Our set of instruments in the first-difference equation includes the values of $\Delta ucc_{i,t}$ and $\Delta s_{i,t}$, lagged at least two periods or earlier if feasible, and the second lag of $I_{i,t}/K_{i,t-1}$. The model is evaluated using the Sargan test of overidentifying restrictions and the Arellano-Bond test. According to both test statistics, our model is correctly specified. The GMM estimation results differ in terms of coefficient sign and significance from both the OLS and FE estimates.

The coefficients of both lags of the dependent variable are positive, a finding that is generally consistent with previous studies (e.g. Chatelain et al., 2001; von Kalckreuth, 2001). However, only the second lag is statistically significant at the 5-percent level. Furthermore, point estimates of sales growth are positive, but statistically not significant. In addition, the long-run elasticity of sales becomes rather small (0.07) and is also statistically not significant. This finding contrasts with the results reported by previous studies, which have confirmed a statistically significant positive effect of sales on investment (Harhoff and Ramb, 2001; von Kalckreuth, 2001; Büttner and Hönig, 2011).[30] Our results imply, that during the observation period, SMEs did not necessarily take contemporary and past changes in their sales into consideration when making investment decisions.

[28] *Point estimates* refers to the coefficients β_m with $m = 0...2$, and σ_n with $n = 0...3$ in model (2.6). They can be interpreted as short-run effects of temporary changes in sales and the user cost of capital growth rates.

[29] Standard errors of η_{ucc} and η_s are computed using the delta method.

[30] Only Dwenger (2014) reports a long-run sales elasticity of similar size (0.09), which was also not statistically significant.

Regarding the point estimates of the user cost of capital growth rate, the coefficients are negative and larger in value than in the OLS and FE estimations. Both the first and second lag of the growth rate are statistically significant at the 10-percent level. The user cost's distributed lag coefficients decline sharply, implying that most of the impact of user cost changes is transmitted within two years. The long-run user cost elasticity is estimated at -0.67, which is larger than the OLS and FE estimates. The value implies that a one-percent decline in the user cost of capital will increase capital by 0.67 percent in the long run.[31] The null hypothesis, which stated that the long-run effect of user cost of capital would be equal to zero, is rejected at the 10-percent level. Our findings – based on the total sample – hence suggest that the basic link between the user cost of capital and business investment has generally functioned during the post-crisis period. This finding implies that declining interest rates had a stimulating effect on business investment through a change in the firms' user cost of capital.

In the next step we augment our baseline model with a categorical variable representing sales expectations, using $BE\_neutral$ for neutral medium-term business expectations and $BE\_negative$ for negative expectations. Positive business expectations ($BE\_positive$) is the reference category. Following Büttner and Hönig (2011) the BE indicators are treated as exogenous. The estimation results for model (2.9) using OLS, the FE estimator and System-GMM are shown in Table 2.5. The coefficients for both business expectations indicators are negative and statistically significant in the OLS and GMM estimations. This finding implies that neutral and negative three-year sales expectations have a negative effect on the capital stock. This is in line with our assumptions.

Our results also show that expectations of declining sales have a larger negative effect than neutral expectations, reducing the capital stock by almost 5.7 percent. An expectation of constant sales reduce the capital stock by 3.8 percent. Our findings are similar to those of Büttner and Hönig (2011), who report that pessimistic expectations about the future decrease the capital stock by about 8 percent. Furthermore, we find that in our extended model, the point estimates of the user cost growth rate increase in value. As a result, the long-run user cost elasticity of capital increases to -0.79, which is statistically significant at the 5-percent level. This implies that the

[31] The results are similar to previous estimates for German corporations (von Kalckreuth, 2001; Harhoff and Ramb, 2001; Büttner and Hönig, 2011; Simmler, 2012; Dwenger, 2014), although the studies used different databases and focused on different time periods.

long-run effect of the user cost of capital is even larger when business expectations are controlled for. As in the baseline model, the long-run elasticity of sales remains small and not statistically significant.

Table 2.5: Results - Model with Business Expectations

$I_{i,t}/K_{i,t-1}$	(1) OLS-BE	(2) FE-BE	(3) GMM-BE
$I_{i,t-1}/K_{i,t-2}$	0.2790***	-0.1665***	0.1252
	[0.0248]	[0.0334]	[0.1152]
$I_{i,t-2}/K_{i,t-3}$	0.1651***	-0.1546***	0.0652**
	[0.0198]	[0.0229]	[0.0297]
$\sum I_{i,t-l}/K_{i,t-l-1}$	0.4441***	-0.3211***	0.1904*
	[0.0259]	[0.0424]	[0.1152]
$\Delta s_{i,t}$	0.0888***	0.0812***	0.0128
	[0.0202]	[0.0294]	[0.0564]
$\Delta s_{i,t-1}$	0.0898***	0.1126***	0.0387
	[0.0172]	[0.0295]	[0.0338]
$\Delta s_{i,t-2}$	0.0281*	0.0649**	0.0091
	[0.0164]	[0.0258]	[0.0218]
η_s	0.3718***	0.1958***	0.0749
	[0.0815]	[0.0588]	[0.1196]
$\Delta ucc_{i,t}$	-0.1014***	-0.0664	-0.2508*
	[0.0369]	[0.0433]	[0.1352]
$\Delta ucc_{i,t-1}$	-0.1157***	-0.0583	-0.1796**
	[0.0388]	[0.0515]	[0.0838]
$\Delta ucc_{i,t-2}$	-0.0860**	-0.1248**	-0.1434**
	[0.0359]	[0.0544]	[0.0691]
$\Delta ucc_{i,t-3}$	-0.0080	-0.0626	-0.0681
	[0.0287]	[0.0386]	[0.0438]
η_{ucc}	-0.5599***	-0.2362**	-0.7928**
	[0.1697]	[0.1161]	[0.4041]
$BE\_neutral_{i,t}$	-0.0153*	-0.0066	-0.0381***
	[0.0093]	[0.0135]	[0.0127]
$BE\_negative_{i,t}$	-0.0269**	-0.0101	-0.0570***
	[0.0128]	[0.0174]	[0.0165]
Observations	3,283	3,283	3,283
AR(1) (p-value)			0.0004
AR(2) (p-value)			0.8857
Sargan test (p-value)			0.4149

Notes: Dependent variable is $I_{i,t}/K_{i,t-1}$. Column (1) is estimated using OLS. Column (2) is estimated using the FE estimator. Column (3) is estimated using System-GMM. The lagged investment–capital ratio, sales and the user cost of capital are treated as endogenous and are instrumented. Instruments are the values (in levels) of $\Delta ucc_{i,t}$ and $\Delta sales_{i,t}$, lagged at least two periods and earlier when feasible, and the second lag of $I_{i,t}/K_{i,t-1}$. Year dummies and a constant are included. Standard errors in parentheses, *p <0.1, **p <0.05, ***p <0.01.

To test whether firms with different business expectations react differently to user cost of capital changes, we re-estimate our baseline model (2.6) for two subgroups: SMEs with positive sales expectations, and SMEs with neutral or negative sales expectations.[32] The GMM estimation results are shown in Table 2.6. As can be seen in column (2) firms with positive sales expectations show a significantly higher user cost elasticity of capital, which is close to unity. The value implies that a one percent decline in the user cost of capital translates to a one percent increase in capital. Firms that expect no sales increases in the next three years, or expect a decline, show a much smaller user cost elasticity of (-0.44). However, the value is not significantly different from zero. Our findings suggest that firms with pessimistic sales expectations (neutral or negative expectations) seem insensitive to changes in the user cost of capital. Monetary policy-induced interest rate changes would, hence, not be effective for these firms. We also find that for both subgroups the long-run elasticity of sales remains statistically not significant.

Past research has shown that estimation results based on GMM are quite sensitive to the set of instruments used (Roodman, 2009b). Furthermore, Eisner and Nadiri (1968) show that estimation results of the long-run user cost of capital effect may vary, depending on the lag-structure choice of the estimation model. As robustness check, we therefore re-estimate the link between the user cost of capital and investment using a parsimonious model which omits the lagged dependent variable and includes only the contemporary changes in sales and the user cost of capital. We estimate this model using the fixed-effects estimator.[33] A similar approach is used by Büttner et al. (2015). The estimation results based on this simple model support the findings of our analysis presented above. The results imply that the link between the user cost of capital and investment has become weaker in the wake of the crisis. Furthermore, the important role of business expectations for investment decisions is confirmed.

Overall, the estimation results of our empirical analysis provide insight into the subdued business investment dynamics of the post-crisis period – despite a substantial decline in the user cost of capital. The results highlight the importance of business expectations for the functioning of the interest rate channel. The persistence of gloomy business expectations among parts of the corporate sector in the post-crisis period – as highlighted by several surveys – have decreased firms' investment directly

[32] We also tested our model for a subgroup of firms with neutral expectations and for a subgroup with negative expectations. However, both estimations suffer from various problems, as indicated by the test statistics. We therefore combine both subgroups of firms.

[33] For more details, see Appendix A.5.

and indirectly. The indirect effect is a dampening of business investment through a lower responsiveness of the firms to changes in the user cost of capital.

Table 2.6: Results - Sample Split by Business Expectations

$I_{i,t}/K_{i,t-1}$	(1) Total	(2) Positive	(3) Neutral/Negative
$I_{i,t-1}/K_{i,t-2}$	0.1102	0.0539	0.0871
	[0.1171]	[0.1176]	[0.1153]
$I_{i,t-2}/K_{i,t-3}$	0.0657**	0.1033**	0.0602*
	[0.0295]	[0.0481]	[0.0319]
$\sum I_{i,t-l}/K_{i,t-l-1}$	0.1759	-0.1572	0.1472
	[0.1164]	[0.1309]	[0.1156]
$\Delta s_{i,t}$	0.0145	0.0400	0.0906**
	[0.0579]	[0.0673]	[0.0425]
$\Delta s_{i,t-1}$	0.0355	0.1051	0.0286
	[0.0339]	[0.0776]	[0.0301]
$\Delta s_{i,t-2}$	0.0065	0.0498	0.0101
	[0.0211]	[0.0423]	[0.0274]
η_s	0.0686	0.2313	0.1517
	[0.1177]	[0.2070]	[0.0964]
$\Delta ucc_{i,t}$	-0.2048	-0.2127	-0.1859
	[0.1332]	[0.1808]	[0.1690]
$\Delta ucc_{i,t-1}$	-0.1554*	-0.3061**	-0.0768
	[0.0828]	[0.1553]	[0.0929]
$\Delta ucc_{i,t-2}$	-0.1287*	-0.2346*	-0.0671
	[0.0687]	[0.1341]	[0.0728]
Δucc_{it-3}	-0.0620	-0.1040	-0.0421
	[0.0431]	[0.0741]	[0.0512]
η_{ucc}	-0.6685*	-1.0173*	-0.4361
	[0.3821]	[0.5694]	[0.4225]
Observations	3,283	1,229	2,054
AR(1) (p-value)	0.0007	0.0061	0.0010
AR(2) (p-value)	0.7486	0.1328	0.9415
Sargan test (p-value)	0.3501	0.2091	0.2397

Notes: Dependent variable is $I_{i,t}/K_{i,t-1}$. Estimated using System-GMM. Instruments are the values (in levels) of $\Delta ucc_{i,t}$ and $\Delta sales_{i,t}$, lagged at least two periods and earlier when feasible, and the second lag of $I_{i,t}/K_{i,t-1}$. Year dummies and a constant are included. Standard errors in parentheses, *p <0.1, **p <0.05, ***p <0.01.

2.5 Conclusion

After the financial crisis and the subsequent sovereign debt crisis, the ECB introduced an ultra-loose monetary policy. The aim was to strengthen aggregate demand and lift the euro area's inflation rate closer to its target rate of 2 percent. To date, the ECB has not yet achieved this goal and questions arise whether the expansionary monetary policy causes more harm than good. Business investment, in particular, remains below pre-crisis levels in most euro area countries. Given the extraordinary monetary stimulus, the subdued development of business investment in Germany after the financial crisis is surprising. Concerns have been raised about whether traditional monetary transmission channels still function properly.

The aim of this paper is to evaluate the functioning of the interest rate channel in the post-crisis period. More specifically, we focus on the relationship between firms' user cost of capital and investment, and test whether business expectations affect this link. We find that during our observation period, the ECB's expansionary monetary policy was quite successful at lowering German SMEs' user cost of capital. Furthermore, we confirm that SMEs significantly responded to user cost changes, with the long-run user cost elasticity of capital ranging between being -0.79 and -0.67, depending on the model. This is similar to elasticity estimates based on data from the pre-crisis period. These findings suggest that the interest rate channel has generally been working during the post-crisis period and that firms are still responsive to user cost changes. However, our empirical analysis also reveals that the results are predominantly driven by SMEs that held positive sales expectations. These businesses react more strongly to user cost changes, with the long-run user cost elasticity of capital being close to unity. By contrast, SMEs that expect constant or declining sales display a much smaller long-run user cost elasticity, which in our analysis does not differ statistically from zero.

Our results confirm the importance of expectations in firms' investment decisions. Pessimistic business expectations, owing to slow economic growth and an uncertain business environment, seem to have been an impediment to business investment activities in Germany in the post-crisis period. Expectations can be regarded as one of the reasons for the seemingly ineffective expansionary monetary policy. Our results also support the view that monetary policy alone cannot fix the euro area's growth problems. To stimulate business investment, more than low interest rates and good access to finance is needed, although both of those factors are important prerequisites. Providing a stable business environment that raises firms' growth expectations is equally important. This leads to questions about the impact that a prolonged period of low interest rates has on long-term growth expectations.

Appendix A

A.1 Neoclassical Investment Theory

The neoclassical investment theory starts from the assumption that a firm's demand for capital is determined by its objective to maximize its net worth which is defined as the integral of discounted net revenues (Jorgenson, 1963). The tax adjusted net revenue of a firm is defined as:

$$R_t = (1-\tau)p_tY_t - p_t^I(1-k-\tau Z)I_t - w_tL_t \tag{A.1}$$

with: p_t = real output price
τ = corporate tax rate
Y_t = $F(K_t, L_t)$ production function with capital K_t and labour L_t
p_t^I = real price of investment goods
k = rate of investment tax credit on new capital purchases
Z = $\int_0^\infty e^{-rt}D_t dt$ is the present value of depreciation allowances D
I_t = $\frac{dK_t}{dt} + \delta K_t$ is gross investment
w_t = wage rate

The net worth of a firm is defined as the discounted stream of earnings (with r being the opportunity cost of capital) and shall be maximized::

$$\begin{aligned}
\max \quad & V = \int_0^\infty [(1-\tau)p_tF(K_t, L_t) - p_t^I(1-k-\tau Z)I_t - w_tL_t]e^{-rt}dt \\
\text{s.t.} \quad & \frac{dK}{dt} = I_t - \delta K_t = \dot{K} \\
& \lim_{t\to\infty} e^{-rt}K_t \geq 0 \\
& K_0 > 0 \text{ given}
\end{aligned} \tag{A.2}$$

Solving the optimization problem we derive the present value Hamiltonian:

$$H = e^{-rt}\big((1-\tau)p_tF(K_t, L_t) - p_t^I(1-k-\tau Z)I_t - w_tL_t\big) + \lambda_t(I_t - \delta K_t) \tag{A.3}$$

where λ_t is the shadow price of one unit of installed capital at time t, representing the contribution of one unit of capital at time t to the value of the firm at time zero. It can thus be regarded as the *present value* shadow price. To get the *current value* shadow price we multiply λ_t with the current value factor e^{rt}:

$$q_t = e^{rt}\lambda_t \tag{A.4}$$

Differentiating H we obtain the following set of first order conditions:

$$\frac{\partial H}{\partial I} = -e^{-rt}p_t^I(1-k-\tau Z) + \lambda_t = 0 \rightarrow -p_t^I(1-k-\tau Z) + q_t = 0 \tag{A.5}$$

$$\frac{\partial H}{\partial L} = ((1-\tau)p_t f_L^{'} - w)e^{-rt} = 0 \rightarrow \frac{w}{(1-\tau)p_t} = f_L^{'} \tag{A.6}$$

$$\frac{\partial H}{\partial \lambda} = \frac{\partial K}{\partial t} = I - \delta K = 0 \tag{A.7}$$

$$\frac{\partial H}{\partial K} = -\dot{\lambda} = e^{-rt}(1-\tau)p_t f_K^{'} - \lambda\delta \tag{A.8}$$

$$\lim_{t\to\infty} \lambda_t K_t = 0 \rightarrow \lim_{t\to\infty} e^{-rt}q_t K_t \tag{A.9}$$

From equation (A.5) we can derive that the current shadow value of one unit of capital q_t should be worth its tax adjusted cost $(1-k-\tau Z)p_t^I$. Equation (A.6) illustrates the condition that real wages $w/(1-\tau)p_t$ shall be equal to the marginal product of labour $f_L^{'}$. Equation (A.7) states that in equilibrium gross investment shall be equal to the depreciation of K. Equation (A.8) illustrates the marginal condition for capital and equation (A.9) the transversality condition. Furthermore, we determine that:

$$-\dot{\lambda} = -\dot{q}e^{-rt} + rqe^{-rt} \tag{A.10}$$

We can thus rewrite equation A.8 as follows:

$$-\dot{q}e^{-rt} + rqe^{-rt} = e^{-rt}(1-\tau)p_t f_K^{'} - \lambda\delta \tag{A.11}$$

If we divide both sides by e^{-rt}, substitute $(1-k-\tau Z)p_t^I = q_t$ in equation (A.11) and solve for the marginal product of capital $f_K^{'}$, we get the following expression:

$$f_K^{'} = \frac{p_t^I}{p_t}\frac{(1-k-\tau Z)}{(1-\tau)}\left(\delta + r - \frac{\dot{p^I}}{p^I}\right) = UCC \tag{A.12}$$

Jorgenson denoted this term the user cost of capital. The rent of one unit of capital must be able to cover the opportunity cost r and the depreciation δ of the unit of capital corrected by the expected capital gains $\dot{p^I}$.

A.2 Capital Demand Equation

Starting point for the empirical model is a CES production function:

$$F(L_{i,t}, K_{i,t}) \equiv S_{i,t} = A_t[\alpha_i K_{i,t}^{-\rho} + (1-\alpha_i)L_{i,t}^{-\rho}]^{\frac{-v}{\rho}} \tag{A.13}$$

with:
$S_{i,t}$ = output defined as net sales
$K_{i,t}$ = capital input
$L_{i,t}$ = labour input
A_t = year specific production technology (productivity)
v = elasticity of scale
ρ = $(1/\sigma) - 1$ determines the elasticity of substitution
σ = elasticity of substitution between capital and labour
α_i = capital share

From equation (A.13) we derive the marginal product of capital:

$$F_K(L_{i,t}, K_{i,t}) = \alpha_i v A_t^{[-\frac{\rho}{v}]} S_{i,t}^{[1+(\frac{\rho}{v})]} K_{i,t}^{[-(1+\rho)]} \tag{A.14}$$

Equalizing the marginal product of capital with the marginal cost $UCC_{i,t}$ we can derive the desired capital stock $K^*_{i,t}$:

$$UCC_{i,t} \equiv \alpha_i v A_t^{[-\frac{\rho}{v}]} S_{i,t}^{[1+\frac{\rho}{v}]} K_{i,t}^{[-(1+\rho)]} \tag{A.15}$$

$$K^*_{i,t} = (\alpha_i v)^{\frac{1}{(1+\rho)}} A_t^{[\frac{(-\rho/v)}{(1+\rho)}]} S_{i,t}^{[\frac{1+(\rho/v)}{(1+\rho)}]} UCC_{i,t}^{[-\frac{1}{(1+\rho)}]} \tag{A.16}$$

$$K^*_{i,t} = (\alpha_i v)^{\sigma} A_t^{[\frac{\sigma-1}{v}]} S_{i,t}^{[\sigma+\frac{1-\sigma}{v}]} UCC_{i,t}^{-\sigma} \tag{A.17}$$

$$K^*_{i,t} = H_t S_{it}^{\beta} UCC_{it}^{-\sigma} \tag{A.18}$$

with: $\mathrm{H}_t = D_i T_t = (\alpha_i v)^{\sigma} A_t^{[\frac{\sigma-1}{v}]}$
$\beta = \sigma + \frac{1-\sigma}{v}$

A.3 Sample Structure

Table A.1: Number of Observations by Year

Year	Observations
2004	520
2005	602
2006	785
2007	896
2008	897
2009	985
2010	952
2011	952
2012	807
2013	688
2014	548
2015	338
Total	8,970

Table A.2: Number of Firms by Sector

Sector	No. of Firms
Accommodation	19
Agriculture	16
Construction	227
Energy and Water	31
Information	13
Manufacturing	434
Mining	2
PA, Education, Healthcare	15
Real Estate	32
Trade	361
Transportation	58
Other Services	42
Technical Services	42

A.4 User Cost of Capital - Data

Price Indices P_t^I and $P_{j,t}$

P_t^I denotes the national price index for investment goods. The data is provided by the German Statistical Office (Fachserie 17/Reihe 2 - Erzeugerpreise gewerblicher Produkte - Investitionsgüter). $P_{j,t}$ denotes the industry-specific output price index. It is derived from industry-specific nominal and real gross-value added data, provided by the German Statistical Office.

Rate of economic depreciation $d_{j,t}$

The industry-specific rate of economic depreciation $d_{j,t}$ is calculated dividing industry-specific economic depreciation by the industry-specific stock of assets. Both data series are obtained from the *Volkswirtschaftliche Gesamtrechnung* (Fachserie 18/Reihe 1.4) provided by the German Statistical Office.

Tax rate τ_t

The annual statutory tax rates on retained earnings (distributed profits) τ_t is calculated following von Kalckreuth (2001).

$$\tau_t = (1 + s_t)\tau_t^r(1 - g_t) + g_t \tag{A.19}$$

with: s_t = solidarity surcharge
τ_t^r = corporate income tax on retained earnings (distributed profits)
g_t = business tax

The data is provided by the German Federal Ministry of Finance. Table A.3 displays the tax parameters used in the user cost of capital calculation.

Table A.3: Tax Parameters 2004-2015

Year	Corporate income tax	Solidarity surcharge	Business tax	τ_t
2004	25%	5.5%	19.4%	40.7%
2005	25%	5.5%	19.5%	40.7%
2006	25%	5.5%	19.6%	40.8%
2007	25%	5.5%	19.4%	40.7%
2008	15%	5.5%	13.6%	27.2%
2009	15%	5.5%	13.6%	27.2%
2010	15%	5.5%	13.7%	27.3%
2011	15%	5.5%	13.7%	27.4%
2012	15%	5.5%	13.8%	27.4%
2013	15%	5.5%	13.8%	27.5%
2014	15%	5.5%	13.9%	27.5%
2015	15%	5.5%	14.0%	27.6%

Notes: Corporate income tax rate refers to taxes on retained earnings and distributed profits. Business tax rate is calculated using the basic federal tax rate (*Steuermesszahl*) – which was 5% until 2007 and 3.5% thereafter – times the average collection rate (*Hebesatz*), which differs year-over-year.

Depreciation Allowances $A_{j,t}$

The industry-specific net present value of depreciation allowances is calculated as the weighted average of asset-specific depreciation allowances (machinery A_t^{Ma} and building A_t^{Bui}).

$$A_{j,t} = w_{j,t}^{Ma} A_t^{Ma} + w_{j,t}^{Bui} A_t^{Bui} \tag{A.20}$$

The weights $w_{j,t}^{Ma}$ and $w_{j,t}^{Bui}$ are industry-specific shares of machinery and building out of fixed assets. The data for is obtained from the *Volkswirtschaftliche Gesamtrechnung* (Fachserie 18/Reihe 1.4) provided by the German Statistical Office.

Depreciation allowances differ by asset type due to different depreciation methods that have to be applied. Buildings are depreciated on straight-line basis. Machinery is also allowed to be depreciated according to the declining-balance method[34] until 2007 and also temporarily in 2009/2010. Rates of depreciation are set in the German income tax law. To be consistent with the German tax system we calculate depreciation allowances for buildings according to the straight-line depreciation method for the total sample period. Depreciation allowances for machinery are calculated according to the declining-balance method until 2010 and according to the straight-line method thereafter. The net present value of allowances according to the declining-balance

[34] The straight-line depreciation method spreads an asset's costs evenly over its 'useful life'. The declining-balance method expenses the asset at a constant rate. Hence, depreciation charges decline each successive period.

and straight-line depreciation method are calculated following ZEW (2014):

$$A^{DB} = \frac{\tau_t \phi_{DB}}{\phi + r} \tag{A.21}$$

$$A^{SL} = \frac{\tau_t \phi_{SL}}{\phi + r}\left(1 - \frac{1}{(1+r)^n}\right) \tag{A.22}$$

with: τ_t = statutory tax rate estimated as in equation A.19
ϕ = allowance rate
r = discount rate
n = life time of asset

We assume a taxation-relevant lifetime, n, of 33.3 years for buildings and of 7 years for machinery. The allowance rate for the declining-balance depreciation method ϕ_{DB} is assumed to be 0.3 for buildings and 0.1429 for machinery. The allowance rate for straight-line depreciation ϕ_{SL} is 0.2 until 2005, 0.3 between 2006 and 2008 and 0.25 in 2009 and 2010.

A.5 Robustness Checks

Our empirical analysis presented above has several limitations. First, the lag-structure of model (2.6) is not theoretically determinable, but must be tested empirically. The lag-length choice is hence fairly arbitrary. Eisner and Nadiri (1968) show that estimation results of the long-run user cost of capital elasticity may vary depending on the choice of the lag-structure. Second, past research has shown that GMM estimations are sensitive to the set of instruments employed (e.g. Roodman, 2009b).

These problems might render our results highly 'model dependent' in the sense of being sensitive to specification choices (e.g. lag-structure and set of instruments). As robustness check, we therefore evaluate the link between the user cost of capital and investment using a parsimonious model that omits any lags:

$$\frac{I_{i,t}}{K_{i,t-1}} = \beta \Delta s_{i,t} + \sigma \Delta ucc_{i,t} + u_{i,t} \tag{A.23}$$

In this model the coefficient β captures the percentage-point change in the investment rate due to a one-percent change in the *level* of sales. Similarly, the coefficient σ captures the percentage-point change in the investment rate due to a one-percent change in the *level* of the user cost of capital.

To test whether firms' responsiveness to user cost changes has declined during the post-crisis period, we interact $\Delta ucc_{i,t}$ with a dummy variable indicating the period after the outbreak of the financial crisis, $Post08_t$. We estimate the following model:

$$\frac{I_{i,t}}{K_{i,t-1}} = \beta \Delta s_{i,t} + \sigma_1 \Delta ucc_{i,t} + \sigma_2 \Delta ucc_{i,t} {*} Post08_t + u_{i,t} \tag{A.24}$$

If the sample firms have been less responsive to user cost changes after 2008, we expect the coefficient of the interaction term to be positive.

In addition, we augment model (A.24) with the business expectation indicator $BE_{i,t}$:

$$\frac{I_{i,t}}{K_{i,t-1}} = \beta \Delta s_{i,t} + \sigma_1 \Delta ucc_{i,t} + \sigma_2 \Delta ucc_{i,t} {*} Post08_t + \alpha BE_{i,t} + u_{i,t} \tag{A.25}$$

Furthermore we estimate equation (A.24) for subgroups of firms that differ in business expectations. We estimate models (A.23) to (A.25) using the fixed-effects estimator.[35]

Table A.4: Robustness Check - Parsimonious Model

	(1) Base	(2) Crisis	(3) BE	(4) Positive	(5) Neutral	(6) Negative
$\Delta s_{i,t}$	0.0434***	0.0432***	0.0375***	0.0387**	0.0324*	0.0525*
	[0.0119]	[0.0118]	[0.0114]	[0.0174]	[0.0195]	[0.0275]
$\Delta ucc_{i,t}$	-0.0278	-0.0695**	-0.0290	-0.1873**	-0.0342	-0.0630
	[0.0211]	[0.0333]	[0.0213]	[0.0801]	[0.0448]	[0.0687]
$\Delta ucc_{i,t}{*}Post08_t$		0.0740*		0.1395	0.0603	0.0408
		[0.0425]		[0.0940]	[0.0619]	[0.0958]
$BE\_neutral_{i,t}$			-0.0275***			
			[0.0083]			
$BE\_neutral_{i,t}$			-0.0413***			
			[0.0100]			
Constant	0.2215***	0.2197***	0.2465***	0.2868***	0.1940***	0.1682***
	[0.0134]	[0.0134]	[0.0146]	[0.0345]	[0.0198]	[0.0265]
Observations	8,321	8,321	8,144	3,059	3,664	1,421
Adjusted R^2	0.0078	0.0082	0.0106	0.0193	0.0016	0.0170

Notes: Dependent variable is the investment rate $I_{i,t}/K_{i,t-1}$. Estimated using fixed-effects model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Year dummies are included. Standard errors in parentheses, $^*p$ <0.1, $^{**}p$ <0.05, $^{***}p$ <0.01.

[35] Results from a Hausman test and an F-test, respectively, suggest that a panel fixed-effects model is to be preferred to both a random-effects panel model and a pooled ordinary least squares model.

The estimation results presented in Table A.4 confirm our previous findings. In the baseline model (column 1) the coefficient of the user cost of capital is not significant. If we control for differences between the pre- and post-crisis period by including an interaction (column 2), we find that effect of user cost of capital changes on the investment rate was negative and statistically significant before 2008. However, after the outbreak of the financial crisis, the relationship became insignificant. Furthermore, the results presented in columns (3) to (6) confirm the important role of business expectations. First, business expectations directly effect the investment rate, the coefficient of both indicators are negative and statistically significant at the 1-percent level. Second, firms with neutral or negative business expectations are insensitive to user cost of capita changes – both during the pre-crisis and post-crisis period.

Chapter 3

Declining Interest Rates and German SMEs' Use of Bank Debt

Abstract

The aim of this paper is to investigate the impact of declining interest rates on the use of bank loans by German small and medium-sized enterprises (SMEs). Assuming that SMEs follow a pecking order when making financing decisions, we theoretically distinguish between an *income* and a *substitution* effect of declining interest rates. A unique firm-level dataset, covering the period 2005 to 2014, enables us to derive SMEs' *desired* share of bank loans in the financing mix of investment projects, and to empirically test the impact of declining interest rates isolated from supply and total demand effects of that decline. The estimation results provide evidence that interest rate reductions have strengthened SMEs' internal financing capacity and reduced their demand for bank loans. A substitution effect (i.e. increased preference for bank loans relative to internal funds) cannot be confirmed for our observation period.

3.1 Introduction

The years leading up to the financial crisis were characterized by a sharp increase in corporate sector debt in the euro area.[1] This development resulted in a severe deleveraging and adjustment process after the crisis. The debt accumulation was largely driven by an excessive use of bank debt, as non-financial corporations (NFCs) shifted away from equity towards debt financing and increased the share of bank loans in their liabilities (ECB, 2013).[2] Understanding the drivers of this development is important, as an excessive accumulation of debt – especially bank debt – by the corporate sector has been identified as a major source of macroeconomic and financial instability (Minsky, 1977; Kindleberger, 1978). Building on the empirical literature about financing decisions by small and medium-sized enterprises (SMEs) (e.g. Coleman, 2006; López-Gracia and Sogorb-Mira, 2008; Mac an Bhaird and Lucey, 2010; Cowling et al., 2012), this paper adds an understanding of the drivers of corporate debt by analysing the connection between interest rates[3] and German SMEs' demand for bank loans.[4]

It has been argued that the increase in corporate-sector debt prior to the crisis was, inter alia, driven by low interest rates and loose financing conditions, causing a vicious cycle of over-investment and over-borrowing (ECB, 2013). Easy monetary conditions and low lending rates have long been known to play an important role in the excessive expansion of credit (Hayek, 1929). On the one hand, low interest rates increase the *supply* of bank credit through their impact on the balance sheets of firms and banks (Bernanke and Gertler, 1995). On the other hand, a decline in interest rates may increase firms' investment spending and thus their *total demand* for finance, including bank debt (Mishkin, 1996).

It remains unclear whether a decline in interest rates increases the demand for all types of finance equally. An assumption underlying most empirical analyses of the effects of monetary policy shocks on the financing mix of companies is that a shock

[1] The debt-to-GDP ratio of euro area non-financial corporations increased from around 60 percent at the beginning of the millennium to a peak of 81 percent at the end of 2008 (ECB, 2012).

[2] A key source of debt financing for euro area NFCs are loans from monetary financial institutions, this applies particularly to small and medium-sized enterprises for which market-based debt instruments such as bonds are generally not available (ECB, 2007).

[3] By *interest rates* we refer to the interest rates NFCs face when borrowing from monetary financial institutions (also called *borrowing costs*), as these are the decisive interest rates for borrowing decisions made by firms.

[4] SMEs account for more than 99% of all corporations in Germany, and are particularly bank dependent. Therefore, they are likely to be an important driver of loans to NFCs.

which works through the conventional interest rate channel will alter the demand for all types of financing equally. In such studies, changes in the relative use of bank debt are seen as reflecting changes in the supply of bank loans caused by the credit channel, rather than by the firm having changed its preference for bank debt (Kashyap et al., 1993; Gertler and Gilchrist, 1993; Oliner and Rudebusch, 1996b). However, experiences prior to the financial crisis indicate that firms may increase their use of bank debt disproportionally to other funds if interest rates decline.

A unique firm-level dataset, covering the period 2005 to 2014, enables us to derive SMEs' *desired* share of bank loans in the financing mix of investment projects. We are hence able to investigate the effect of declining interest rates on firms' use of bank loans, isolated from supply effects, and the total demand effects of that decline. Starting from the assumption that SMEs follow a pecking order when making financing decisions, we empirically test whether interest rate reductions *increase* firms' use of bank debt by increasing firms' preference for bank loans relative to internal funds. We also test the counterhypothesis that declining interest rates *reduce* firms' demand for bank loans because – owing to declining interest expenses – firms' internal financing capacity is strengthened (Mishkin, 1996). To our knowledge, no other studies have examined the manner in which declining interest rates might trigger substitution or income effects. Our results provide insight into the consequences of a prolonged period of low interest rates for the corporate sector's demand for bank debt.

3.2 SME Financing Decisions and the Role of Interest Rates

To finance their daily operations and investment projects, firms can choose from a variety of funds. These funds differ in terms of their source (internal versus external) and the legal position of the capital provider (equity versus debt) (Bundesbank, 2012). The choice is influenced by various firm-specific factors but also by the macroeconomic environment, which determines the availability and price of the different types of funds.

3.2.1 Corporate Finance Theories

Corporate financing decisions have been the focus of extensive research for several decades. Modigliani and Miller (1958) argue that in the absence of taxes, transaction costs, bankruptcy costs and asymmetric information, a firm's market value and weighted average cost of capital are unaffected by the firm's capital structure. Entrepreneurs would thus be indifferent about debt or equity financing. Internal funds and external debt would be perfect substitutes (Vanacker and Manigart, 2010). In the following decades, two competing capital structure theories emerged that relaxed Modigliani and Miller's (1958) assumptions.

The *trade-off theory* argues that firms seek to reach a target debt level which balances the costs and benefits of an additional unit of debt (Frank and Goyal, Frank and Goyal). Advantages of using debt derive from interest payments being deductible from taxable profits (Modigliani and Miller, 1963).[5] However, these tax benefits are offset by rising bankruptcy costs as the increased indebtedness raises the risk of financial distress (Kraus and Litzenberger, 1973).[6] The *pecking order theory* (POT) incorporates asymmetric information and incentive problems among the capital providers and the firm's management, and predicts a hierarchical order of financing instruments (Myers, 1984; Myers and Majluf, 1984). Aiming to minimize adverse selection costs, firms prefer internal funds (e.g. retained earnings) over external funds. If external finance is needed, firms prefer low-risk short-term debt followed by riskier long-term debt. The last option is external equity raised by the emission of stocks (Donaldson, 1961; Myers and Majluf, 1984). Most importantly, the POT sees the use of debt as reacting passively to changes in a firm's internal funds (Opler et al., 1999).

In the traditional corporate finance literature, no particular distinction is made between firms of different sizes. However, differences in regulatory and institutional conditions as well as operating practices lead to considerable divergence in financial decision-making for large versus small firms (Brighi and Torluccio, 2007). Empirical studies on corporate finance have documented the differing financing behaviour (Rajan and Zingales, 1995; Fama and French, 2002). Groves and Harrison (1974) argue that the 'finance gap' between large and small enterprises is due to a 'supply gap' and a 'knowledge gap'. The supply gap stems from the observation that certain funds are either not available or are more costly for small firms, owing to greater

[5] See Graham (2003) for a general overview on taxes and corporate finance.

[6] Financial distress is defined as 'the inability of a firm to pay its financial obligations as they mature' (Beaver, 1966, p.71).

informational asymmetries.[7] Higher external finance premiums[8] leave SMEs at a disadvantage when trying to raise external funds. Financial intermediaries are generally able to overcome informational asymmetries more effectively than financial markets can, and can thus provide funds to SMEs at better terms (Diamond, 1984; Berger and Udell, 1998). In addition, the transaction and regulatory costs of issuing publicly traded equity or debt are high enough to generally discourage SMEs from issuing shares or bonds (Coleman, 2006). Thus, small firms do not have access to the full range of funding sources that large companies can access. In addition to this supply gap, SMEs are sometimes not even aware of the full scope of possible funding sources; this is known as the knowledge gap (Holms and Kent, 1991). As a result SMEs tend to depend on internally generated funds, informal funding sources (e.g. family and friends), bank loans, trade credit and government-subsidized loans (Berger and Udell, 1998).

Alternative approaches related to Myers' (1984) pecking order concept emphasize the role of the entrepreneur in the financial decision making process of SMEs. Small and medium-sized enterprises are generally organized in different legal forms and have different ownership structures compared with large companies. For example, sole proprietorship and partnership are commonly favoured by SMEs, and management and ownership are often the same entities within an SME. This gives rise to a strong influence of owner preferences on financing decisions (Norton, 1991; Achleitner et al., 2011). Holms and Kent (1991) argue that owners prefer funding sources that will minimally dilute their ownership or control of the firm. This particularly applies to internal funds.

In line with these theoretical considerations, many empirical studies have shown that SMEs follow a preference order when making financing decisions (e.g. Chittenden et al., 1996; Michaelas et al., 1999; Lopez-Gracia and Aybar-Arias, 2000; Mac an Bhaird and Lucey, 2010). To finance their daily operations and investment projects, SMEs mainly rely on internal financing sources followed by external borrowing from financial intermediaries. Capital market financing is rarely used.

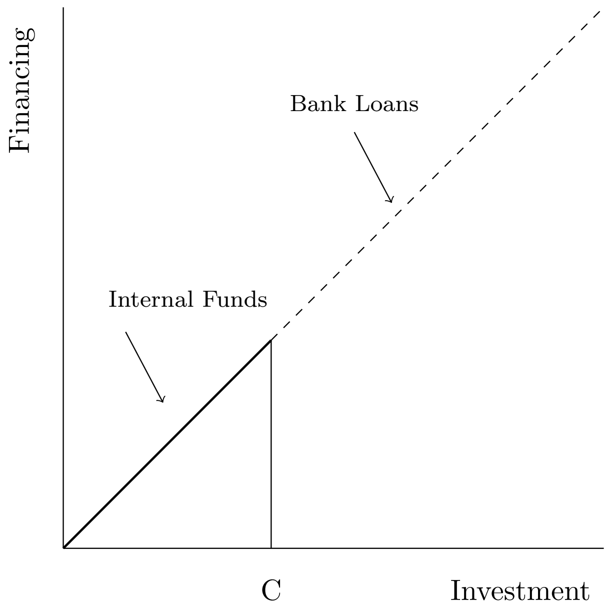
[7] Informational opacity is a defining characteristic of small business finance, as information about contracts, projects, customers and so on is generally not publicly available as it is for larger firms (Berger and Udell, 1998). Hence, the problem of asymmetric information is more severe for SMEs, which are relatively unable to signal their creditworthiness.

[8] The external finance premium reflects the lender's expected costs of monitoring, evaluation and information collection (Bernanke and Gertler, 1995).

3.2.2 SME Financing Decisions: a Simple Model

We subsume the characteristics of SME financing decisions as discussed above into a simplified model for SME investment financing, illustrated in Figure 3.1.

Figure 3.1: SME Financing Hierarchy



Notes: Own illustration based on Leary and Roberts (2010).

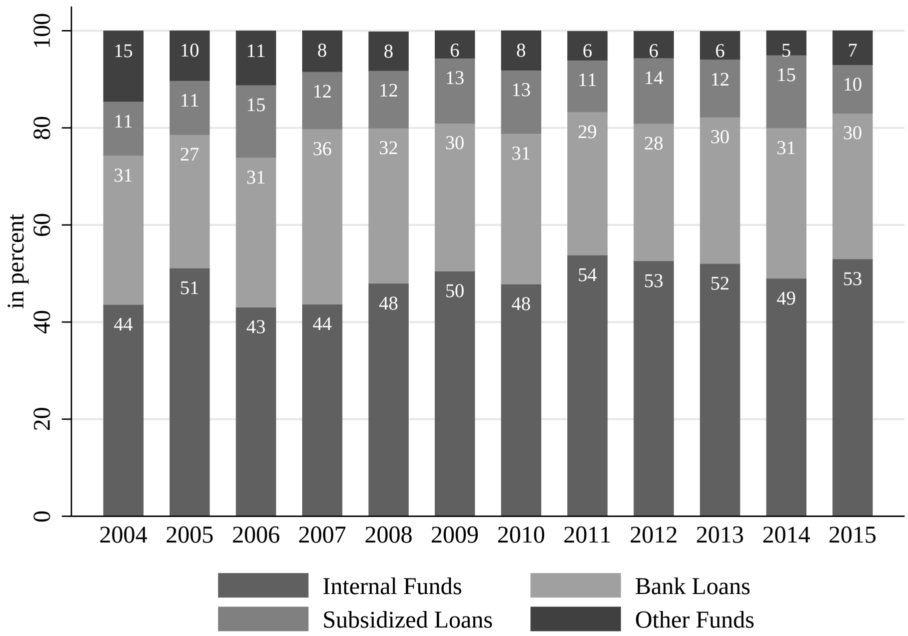
Assuming that SMEs follow a pecking order when making financing decisions, a firm will first draw on its internal funds before turning to external funds. It will finance its investment project with internal sources up to the threshold C, which we define following Leary and Roberts (2010) as the point at which the investment volume equals the amount of internal funds the firm is willing to employ:

$$0 = Investment_{i,t} - ((1 - \alpha_{i,t}) * InternalFunds_{i,t}) \tag{3.1}$$

where $Investment_{i,t}$ denotes the size of the investment project of firm i in year t, $InternalFunds_{i,t}$ denotes the firm's total available internal funds and $\alpha_{i,t}$ is the share of total available internal funds the firm does not want to use for financing investment projects.

In a literal interpretation of the POT, $\alpha_{i,t}$ equals 0. That is, the firm would first exhaust all internally available funds before using external funds. However, Myers (1984) argues that although firms generally follow a certain pecking order when making financing decisions, they might consider using funds of a lower preference order if the associated benefits (e.g. tax advantages) outweigh the cost of asymmetric information. Furthermore, firms may wish to retain a certain reservoir of internal funds to ensure that profitable future investment opportunities can be realized even when cash flow is low and alternative funds are too expensive (Ferreira and Vilela, 2004).[9] Hence, $\alpha_{i,t}$ can lie between 0 and 1.

Figure 3.2: SME Financing Mix (2004-2015)



Source: KfW. Share of financing instruments in the realized financing mix of German SMEs' investment projects.

If the size of the investment project exceeds the threshold C in Figure 3.1, the firm has to turn to external financing sources to cover its financing needs. Given the limited access to the capital market and the resulting dependency of SMEs on banks, we assume that SMEs cover their external financing needs for investment projects almost entirely through bank loans. Data from German SMEs' realized financing mix for investment projects support this assumption: on average, around 80 percent of an investment project is financed with internal funds (50 percent) and bank loans (30 percent) (Figure 3.2). A further 12 percent is financed with subsidized loans and a mere 8 percent with other funding sources, such as venture capital or mezzanine

[9] Stafford (2001) finds empirical evidence that firms do not minimize the use of external funds by initially exhausting internal funds as the POT predicts. Viswanath (1993) shows that strategic long-term considerations can lead firms to prefer external funds despite having enough internal funds available.

capital.[10,11]

Hence, we define a firm's latent bank loan demand $D^*_{i,t}$ as the difference between the investment project amount and the amount of internal funds that the firm is willing to employ:

$$D^*_{i,t} = Investment_{i,t} - ((1 - \alpha_{i,t}) * InternalFunds_{i,t}) \tag{3.2}$$

However, the actual observed loan demand $D_{i,t}$ (which is observable in the firm's loan application) may differ from the latent loan demand $D^*_{i,t}$. The reason is that firms are sometimes reluctant to apply for a bank loan owing to the fear of being rejected (Levenson and Willard, 2000). In such cases the latent bank loan demand $D^*_{i,t}$ is larger than 0 but the observed loan demand $D_{i,t}$ equals 0. The decision to apply for a bank loan to finance the investment project is governed by the following equation:

$$APPLY_{i,t} = \begin{cases} 1, & \text{if } D^*_{i,t} > 0 \wedge DISC_{i,t} = 0. \\ 0, & \text{if } D^*_{i,t} = 0 \vee (D^*_{i,t} > 0 \wedge DISC_{i,t} = 1). \end{cases} \tag{3.3}$$

where $DISC_{i,t}$ takes the value of 1 if the firm feels discouraged from applying for a bank loan. An increase in the loan application rate is observed if (a) firms switch from feeling discouraged to feeling encouraged to apply for a bank loan, or (b) the latent loan demand increases from $D^*_{i,t} = 0$ to $D^*_{i,t} > 0$. Given the firm has applied for a bank loan, the observed *desired* bank loan share in the finance mix is defined as follows:

$$SHARE_{i,t} = D_{i,t}/Investment_{i,t} \tag{3.4}$$

The observable desired loan share $SHARE_{i,t}$ increases if ceteris paribus $D_{i,t}$ increases.

3.2.3 SME Financing Decisions and Interest Rates

A structural decline in interest rates can alter the above described financing decisions of SMEs in several respects. First, it can impact the firm's willingness to apply for a bank loan ('encouragement effect'). Second, it can affect the availability of internal funds that the firm can employ to finance the investment project ('income effect').

[10] Mezzanine capital is a hybrid of debt and equity financing.

[11] Although the use of bonds has become increasingly popular among German SMEs, these so-called *Mittelstandsanleihen* are still limited to a comparatively small number of rather large SMEs.

Third, it can influence the firm's willingness to substitute internal funds for external funds by altering $\alpha_{i,t}$ ('substitution effect').

Encouragement Effect

Assuming positive application costs and imperfect screening by banks, Kon and Storey (2003) show that firms are discouraged from applying for a bank loan when the effective costs of borrowing exceed the firm's expected return on investment ROI. The firm's decision to approach a bank depends on the loan interest rate R, the opportunity costs OC[12], the application costs AC[13] and the bank's screening error se[14]. The formula is as follows:

$$ROI = R + OC + \frac{AC}{1 - se} \tag{3.5}$$

Kon and Storey (2003) argue that bank application rates are high when (a) the costs of alternative sources of finance are high, (b) application costs are low, (c) the expected return on investment is high, and (d) the interest rate R is low.[15] It can be concluded that:

H 1 *If the encouragement effect holds, a reduction in interest rates has ceteris paribus a positive effect on the loan application rate.*

Income Effect

Interest rate changes can substantially affect a firm's liquidity position and hence its internal financing capacity. This transmission mechanism of monetary policy-induced interest-rate changes on a firm's financial position and real spending activities is called the *balance sheet channel* (Bernanke and Gertler, 1995). To finance inventory and working capital, firms mainly rely on short-term and floating debt. Therefore, an interest rate change directly affects a firm's cost of new and outstanding debt

[12] Opportunity costs are defined as the net return after interest payments that are yielded if the project was financed by other external capital providers (e.g. money lenders). It is assumed that other lenders charge higher interest rates than the banks (Kon and Storey, 2003).

[13] According to Kon and Storey (2003), application costs include financial costs (incurred to provide the bank with required information), in-kind costs (due to time spent on the application process) and psychic costs (due to discomfort in passing information about the firm or its owners to a third party).

[14] The value of se lies between 0 and 1 and can be regarded as the probability that a bank cannot perfectly distinguish 'good' from 'bad' borrowers.

[15] For the U.S. Ferrando and Mulier (2015) provide empirical evidence that lower loan interest rates reduce the probability of firms feeling discouraged from bank lending.

and hence its interest expenses. If interest expenses decline, the firm's profit and cash flow increase, which in turn strengthens the firm's internal financing capacity (Mishkin, 1996).[16] This argument can be summed up in the following hypothesis:

H 2 *The availability of internal funds is c.p. negatively related to the level of interest rates.*

If SMEs follow the POT sequence and first draw on internal funds, and if interest rate reductions increase SMEs' internal funds, we can conclude that:

H 3 *If the income effect dominates, a reduction in interest rates will c.p. decrease the loan application probability and will also decrease the desired bank loan share in the financing mix.*

Substitution Effect

From equations (3.2) to (3.4) it can be derived that the loan application probability and the desired loan share are inversely related to the share of internal funds the firm wishes to retain ($\alpha_{i,t}$). As mentioned in the preceding section $\alpha_{i,t}$ may be influenced by the firm's desire to keep a cash reserve in order to finance future investment projects, as well as by cost-benefit considerations concerning funding sources that would normally be lower in the order of preference.

According to the trade-off model of cash holdings, firms equate the cost and benefits of holding cash (Opler et al., 1999). As interest rates decline, the opportunity costs of holding cash decline – and the direct costs of bank debt also decrease. At the same time the expectation of future interest rate hikes – owing for instance to a monetary policy tightening – that could make bank debt more expensive or even unavailable raises the benefits of holding cash. These cost-benefit considerations of cash holdings could induce firms to retain more cash and switch to bank loans when interest rates are low and loans are easily available. This can be particularly true for SMEs which are financially constrained.[17]

[16] The impact of interest rate changes on a firm's financial position has been widely confirmed in empirical studies. Simulating a tightening of monetary policy, Bernanke and Gertler (1995) show that over 40 percent of the subsequent short-term decline in corporate profits is the direct result of the increase in interest payments. Ippolito et al. (2015) provide empirical evidence that firms which use more bank debt and do not hedge against interest rate risks show a strong sensitivity of their interest expenses and cash flow with respect to interest rate changes.

[17] Using a panel of 860 small and medium-sized firms from Spain during the period 1996–2001 García-Teruel and Martínez-Solano (2008) show that SMEs increase (decrease) their cash holdings if interest rates drop (rise).

If firms take advantage of favourable financing conditions by substituting internal funds for bank debt to top up cash holdings for future investment opportunities, we can conclude that:

H 4 *If the substitution effect dominates, a decline in interest rates c.p. increases the loan application probability and the desired bank loan share in the financing mix.*

To sum up, our theoretical considerations show that the effect of interest rate reductions on the bank loan application rate and the desired loan share are ambiguous. A predominant encouragement effect and substitution effect would lead to an increase in loan application rates and in the desired bank loan share if interest rates decline. If the income effect is stronger, a reduction in interest rates will cause a decline in the relative use of bank debt and a concomitant drop in the probability of loan applications.

In the following sections, we test the derived hypothesis with regard to German SMEs. Using aggregate data we first analyse how financing conditions and corporate sector borrowing have covaried in the past 15 years, during which period interest rates have declined owing to an increasingly expansionary monetary policy.

3.3 Financing Conditions and Corporate Sector Borrowing in Germany

The ECB's monetary policy since the early 2000s was driven by a sequence of crises – the dot-com crash in 2000, the financial crisis in 2008 and the sovereign debt crisis in 2012 – and has resulted in an unprecedented decline in interest rates in the euro area. This has significantly influenced borrowing costs and firms' access to funds. If interest rates influence firms' financing decisions these developments should be somehow reflected in aggregate loan data and SMEs' financing mix.[18]

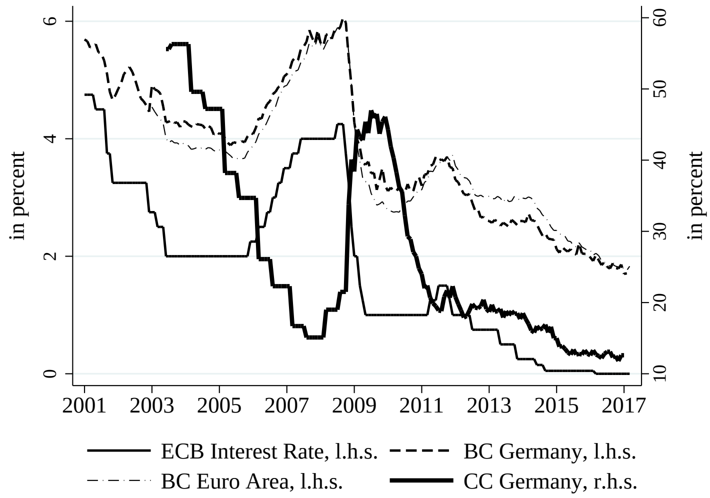
3.3.1 Pre-Crisis

The period of the run-up to the financial crisis (2001-2007) was characterized by a rather accommodative monetary policy in the euro area. Due to the economic down-turn that followed the bursting of the dot-com bubble in 2001 the ECB had gradually lowered its key interest rate from 4.75 percent at the end of 2001 to 2

[18] The SMEs' financing mix discussed in this section is the *realized* financing mix, hence the result of demand and supply of the different sources of funds. The share of bank loans in the financing mix is therefore not necessarily the *desired* share of bank loans.

percent in June 2003 - a historic low at that time (Figure 3.3). It remained at this level until the end of 2005. Short-term and long-term lending rates in Germany and other euro area countries closely followed the path of the monetary policy rate and continuously fell until 2005.

Figure 3.3: Borrowing Costs and Credit Constraints of NFCs

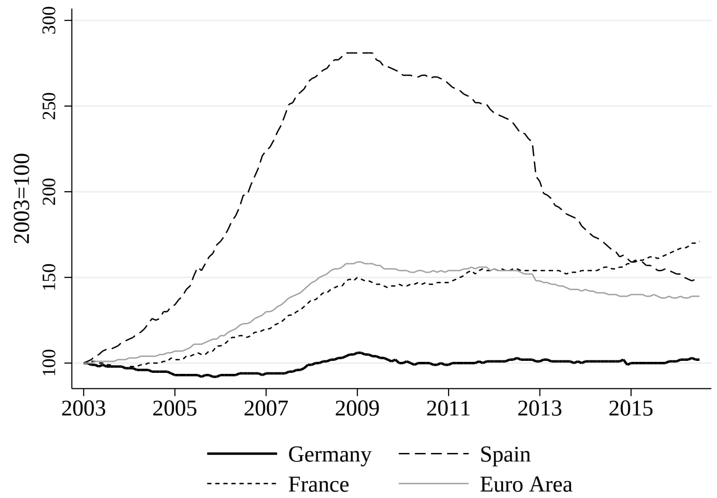


Source: ECB, Ifo. ECB Interest Rate - interest rate on the main refinancing operations. BC - borrowing costs for NFCs. CC (credit constraints) - share of manufacturing sector firms reporting restrictive lending by the banks.

Borrowing costs for NFCs in Germany – that is, the weighted average of interest rate charged to NFCs on new loans – declined from around 6 percent in 2000 to less than 4 percent in mid-2005, which was still slightly higher than the euro area average (Figure 3.3). Owing to recovering economic growth and increasing inflationary pressure in the euro area since 2006, the ECB gradually raised the key interest rate to 4 percent by June 2007. Borrowing costs for German NFCs started to increase again and reached a high of around 6 percent in mid-2008.

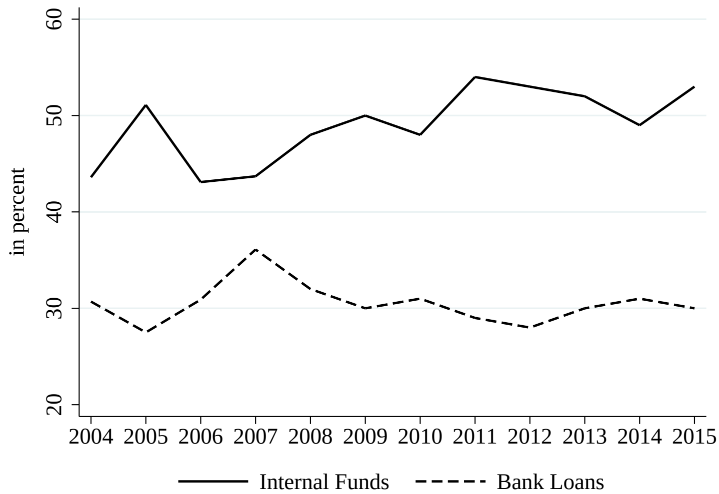
Whereas declining interest rates in the pre-crisis period had spurred borrowing by NFCs in many euro area countries, causing an increase of private-sector debt, Germany experienced a steady decline in loans to the corporate sector between 2001 and mid-2005 (Figure 3.4). This development is also reflected in the financing mix of German SMEs (Figure 3.5). The share of bank loans in the financing mix of new investment projects declined to a low of 27 percent in 2005, whereas the share of internal funds increased to roughly 51 percent. Borrowing by NFCs in Germany increased only as of 2006 once interest rates had already increased. Between the end of 2005 and the end of 2008 the number of outstanding loans to NFCs increased

Figure 3.4: Bank Lending to NFCs in Selected Euro Area Countries



Source: ECB. Loans to NFCs by domestic monetary financial institutions.

Figure 3.5: Share of Internal Funds and Bank Loans in SMEs' Financing Mix

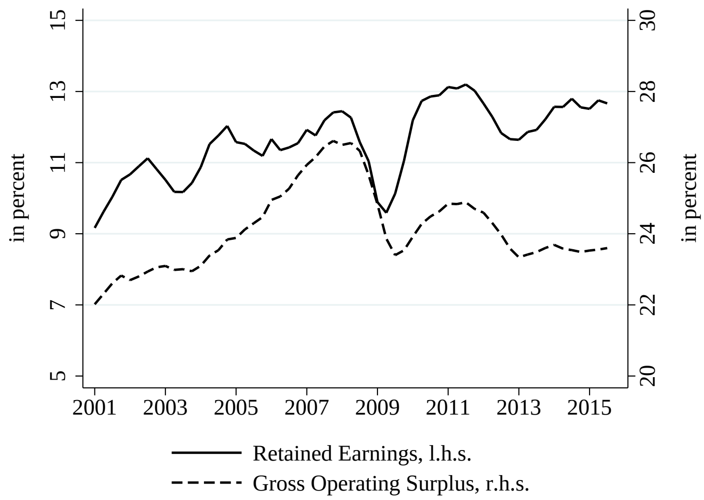


Source: KfW. Share of internal funds and bank loans used to finance investment projects of German SMEs. Data only available after 2003.

by 15 percent. Among SMEs, the share of bank loans in the investment financing mix increased from 2005 to 2007 by almost 10 percentage points, to 36 percent. Simultaneously, the share of internal funds dropped to 44 percent in 2007.

The pre-crisis development of German SMEs' financing mix as well as aggregate corporate-sector borrowing seem not to support the prevalence of a strong substitution effect (as described in the preceding section). This is in contrast to other euro area countries and might be attributed to three main reasons. Firstly, the pre-crisis

Figure 3.6: Internal Funds of German NFCs



Source: Eurostat. Four-quarter moving sums. Gross operating surplus captures firms' operating income – that is, gross value added minus the cost of production. Retained earnings is proxied using corporate savings (operating surplus and the financial income of NFCs, after interest payments, dividends, rents and corporate taxation)(ECB, 2013).

differences in aggregate borrowing partly reflect diverging economic developments in euro area core and periphery countries (Schnabl and Wollmershäuser, 2013). Whereas the periphery experienced strong economic growth after the turn of the millennium, Germany slipped into a recession in 2003 and grew only moderately in 2004 and 2005. Weak economic growth was accompanied by weak corporate investment activities, dampening the overall demand for financing – particularly external financing. (Bundesbank, 2012). The ECB's Bank Lending Survey (BLS) indicates that low investment demand was a major reason for low credit demand in Germany until 2005.

Secondly, the ECB BLS results indicate that since around 2004, German firms increasingly substituted bank loans for alternative funds, particularly internal funds. This substitution process was spurred by the firms' strategies to strengthen their equity base and by rapid growth in profits, which increased the firms' internal financing capacity (Figure 3.6) (Bundesbank, 2012, 2014). This pattern suggests that the declining share of bank loans in SMEs' financing mix until 2005 might have been partly caused by an income effect of declining interest rates.

Thirdly, although borrowing costs for German NFCs declined, banks were reluctant to supply credit. In mid-2003 more than half of the manufacturing sector firms signalled significant credit constraints (Ifo, 2016). Firms' credit access improved considerably after 2003; however, at the end of 2005 around a third of all companies still faced credit constraints. Hence, the declining share of bank loans as well as the total number of NFC loans until 2005 might also have been influenced by supply restrictions.

3.3.2 Crisis

The financial tensions that turned into a global financial crisis in September 2008 brought a sudden stop to the accelerated economic growth in Germany and the rest of the euro area. To sustain financial intermediation and the availability of credit to the private sector, monetary authorities worldwide reduced interest rates to unprecedented low levels and implemented non-standard policy measures (ECB, 2010b). The ECB's key interest rate was lowered to 1 percent throughout 2009. Borrowing costs of the German corporate sector fell considerably, from around 6 percent in September 2008 to 3.2 percent at the end of 2009 (Figure 3.3).

Despite the immediate measures taken by the ECB, lending in the euro area contracted in 2009. NFC borrowing in Germany continued to increase throughout 2008 but collapsed at the start of 2009. The share of bank loans in the investment financing mix of German SMEs dropped from 36 percent in 2007 to 30 percent in 2009. The decline in corporate sector borrowing was on the one hand caused by a rather sharp fall in the demand for finance, as the German economy was severely hit by the crisis. Real gross domestic product (GDP) declined by 5.6 percent in 2009, and gross fixed capital formation in all sectors fell by more than 10 percent in real terms, dampening the demand for external finance (Destatis, 2016). On the other hand, the supply of credit contracted. In mid-2009, around 45 percent of manufacturing-sector firms signalled that lending conditions were restrictive. The limited availability of external funds such as bank loans increased firms' reliance on internally generated funds. The share of internal funds in the financing mix of SMEs increased from 44 percent in 2007 to 50 percent in 2009.

3.3.3 Post-Crisis

Monetary policy decisions in the euro area after the financial crisis were influenced by the perpetuation of the sovereign debt crisis, the staggering economic recovery in the euro area, and the gradual fall of the inflationary expectations that cumulated in a fear of deflation. Owing to sluggish growth and subdued inflation in the euro area, the key interest rate was gradually lowered to 0 percent. The cost of borrowing for German NFCs fell from 3.2 percent at the end of 2009 to 1.71 percent in February 2017 (Figure 3.3).

However, the number of outstanding loans to the corporate sector in Germany increased only slightly until 2016. The subdued credit growth is rather surprising as there were – in contrast to the period 2003–2005 – no indications of credit restrictions. Credit supply improved considerably as of 2010 and was soon back to pre-crisis levels. In addition, contrary to other euro area countries, the German economy quickly recovered from the financial crisis and output grew substantially in 2010 and 2011. Nevertheless, the subdued investment demand has dampened the demand for external finance such as bank loans in the wake of the financial crisis (Bundesbank, 2013). However, even if firms invested, historically low lending rates and good access to finance seem not to have encouraged German NFCs to use more bank debt or to increase the share of bank loans in their financing mix. The share of bank loans in the investment financing mix of SMEs remained at around 30 percent between 2010 and 2015. As a corollary, SMEs increased the share of internal funds in their financing mix to a record high of 54 percent in 2011 (Figure 3.5). In 2015 it was still at 53 percent.

The results of this section show that corporate sector borrowing in Germany has shown few dynamics in the past 15 years despite favourable credit conditions in many years. Looking at aggregate data on loans and SMEs' financing mix, the interest rate changes seem not to have triggered a substitution effect. It rather seems that a positive income effect of declining interest rates has, at times, dampened firms' demand for bank loans.

3.4 Empirical Analysis

Aggregate data, as presented in the preceding section, might not necessarily reflect changes in firms' preferences for bank loans, as they reflect supply and demand changes. In this section, therefore, we proceed our analysis using firm-level data of German SMEs to evaluate the impact of interest rate reductions on SMEs' use of bank loans. In the analysis we test for an income and substitution effect.[19]

[19] Due to data limitations we cannot test for an explicit encouragement effect of interest rate reductions.

3.4.1 Data

The basis of our empirical analysis is the *KfW Mittelstandspanel*, a representative annual survey that covers German micro, small and medium-sized enterprises with less than EUR 500 million annual turnover. The database comprises qualitative and quantitative data from 60,653 firms over a period of 14 years (2002–2015). In addition to firm-level characteristics, the dataset includes information on planned investment activities and bank loan applications.

We discard firm-year observations that belong to the 1st or 99th percentile of the variables of interest to control for outliers. Taking into account missing observations, our final sample contains 18,090 observations from 8,274 SMEs for the period 2005–2014.[20] The sample covers a period during which nominal and real interest rates declined to unprecedented low levels.[21] The sample is unbalanced owing to missing data as well as varying participation behaviour by the firms. Appendix B.1 contains more information on the sample structure.

Our analysis of SMEs' financing decisions differs from that of other studies, as we do not focus on the corporate capital structure but rather on SMEs' incremental financing decisions. The capital structure of a firm reflects aggregated past financing decisions, whereas the financing mix of a particular investment project reflects the immediate entrepreneurial decision given the prevailing financing conditions. In the survey the firms are asked whether they applied for a bank loan to finance their planned investment projects. Given this information, we construct the variable $APPLY$, which equals 1 if the respective firm applied for a bank loan and 0 if it did not. We find that in years when interest rates[22] declined, the average loan application rate was 43.5 percent. In all other years the average rate was 44.3 percent (Figure 3.7). Descriptive statistics thus indicate that in the sample period, SMEs were less likely to apply for a bank loan when interest rates declined, although the difference is statistically not significant.[23]

Furthermore, the firms are asked to state the amount they wanted to borrow to finance investment projects. These data allow us to derive the *desired* bank loan

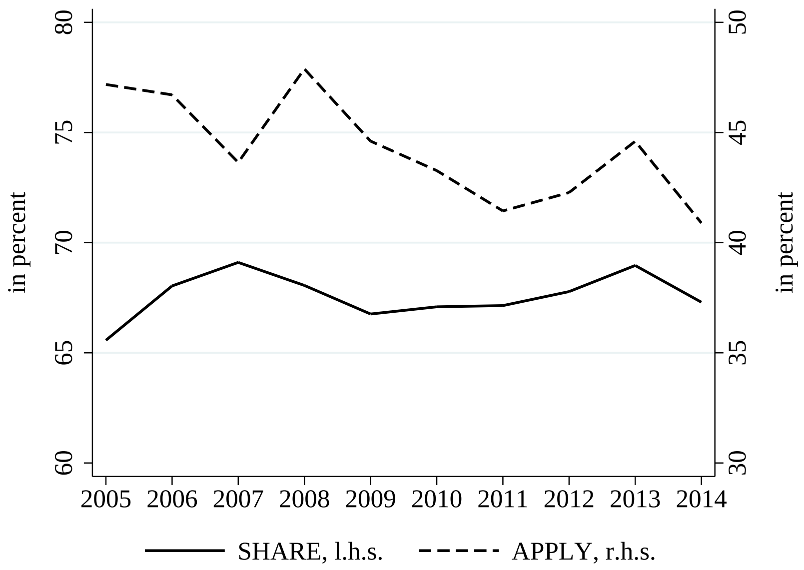
[20] Our estimation sample covers less years than the original sample due to some variables being not available for all survey years.
[21] The main refinancing rate of the ECB declined from 2 percent in 2005 to 0.05 percent in 2014.
[22] Defined as borrowing costs of NFCs as explained below.
[23] A t-test was conducted. The p-value of 0.2603 indicates that the null hypothesis, which states that the difference is equal to 0, cannot be rejected.

share in the financing mix, defined as:[24]

$$SHARE = \frac{\text{amount of loan applied for}}{\text{planned investment volume}} \tag{3.6}$$

As we focus on the *desired* rather than the *realized* loan share in the financing mix we are able to study the effect of interest rate reductions on firms' preferences for bank loans, isolated from supply side effects of the reduction. Descriptive statistics show that during years when interest rates declined, the average desired bank loan share was 68.1 percent (Figure 3.7). During years of interest rate increases, the average share was only slightly higher at 68.8 percent. A t-test shows no significant difference in the means of $SHARE$ between periods of declining versus increasing interest rates (p-value of 0.2503).

Figure 3.7: Desired Loan Share and Loan Application Rate (2005-2014)



Notes: APPLY: share of sample firms that applied for a bank loan to finance investment projects. SHARE: average desired share of bank loans in the financing mix of investment projects.

In addition to information on investment activities and loan applications, our dataset includes firm-specific balance sheet and income statement data. Given this information we can construct a proxy variable for the amount of internal funds that the firm had available to finance its investment projects. The POT literature

[24] $SHARE$ is only measured for those firms that applied for a bank loan, hence it is always larger than zero.

often refers to the *stock* of internal funds, such as cash and marketable securities (e.g. Vanacker and Manigart, 2010). As our dataset does not include stock information, we approximate the amount of internal funds using the firm's cash flow to total assets ratio, CF (e.g. Oliner and Rudebusch, 1996a; Shyam-Sunder and Myers, 1999; López-Gracia and Sogorb-Mira, 2008).

3.4.2 Estimation Framework

Based on the dataset described above, we test – in three steps – for the existence of an income and substitution effect of interest rate reductions. In the first step we test the validity of the POT by analysing how the availability of internal funds influences SMEs' decision to apply for bank loans, and the desired bank loan share in the financing mix:

$$APPLY_{i,t} = \beta_0 + \beta_1 CF_{i,t-1} + \beta_2 Y_{i,t} + \lambda_{j,t} + \epsilon_{i,t} \tag{3.7}$$

$$SHARE_{i,t} = \beta_0 + \beta_1 CF_{i,t-1} + \beta_2 Y_{i,t} + \lambda_{j,t} + \epsilon_{i,t} \tag{3.8}$$

where $APPLY_{i,t}$ is a dummy variable taking the value of 1 if the firm applied for a bank loan and 0 if not; $SHARE_{i,t}$ is the desired share of bank loans in the financing mix of an investment project; $CF_{i,t-1}$ is the cash flow to total asset ratio as a proxy for the amount of internal funds, lagged by one year to mitigate the possibility of simultaneity. If the POT holds, we expect the coefficient of $CF_{i,t-1}$ to be negative. That is, greater internal funds would reduce the probability of a SME applying for a bank loan and would also reduce the desired bank loan share.[25]

$Y_{i,t}$ is a vector of firm specific control variables. It comprises variables commonly found in the capital structure literature to describe the firm's structural and financial characteristics as well as information asymmetries. We include the debt to total assets ratio LEV, which captures the firm's debt capacity (e.g. Vanacker and Manigart, 2010). We expect the coefficient to be negative, because companies with higher leverage may have difficulty serving additional debt-related payments, and may therefore abstain from applying for a bank loan and decrease their desired bank loan

[25] As the dependent variable $SHARE_{i,t}$ is only observable if $APPLY_{i,t}$ is equal to 1 (i.e. the firm applied for a bank loan), we might face a selection bias. We rule out selection problems by estimating a sample selection model as a robustness check (see Appendix B.3)

share. To capture tax shields[26] we include non-debt tax shields, $NDTS$, defined as depreciation over total assets (e.g. Bradley et al., 1984). Firms can reduce their tax burden and simultaneously avoid financial distress costs by using more non-debt tax shields. Higher non-debt tax shields are thus expected to make firms less interested in bank debt (Michaelas et al., 1999).

We further include the expected cost of financial distress of a firm, determined by the probability of default and the expected loss in the case of default (Myers, 1984). Default probability is captured by the firm's creditworthiness, CW, measured by the *Creditreform Creditworthiness Indicator* at the beginning of year t.[27] As a proxy for the cost of financial distress, we include the fixed to total assets ratio, FA (Vanacker and Manigart, 2010). A lower ratio indicates higher costs of financial distress and thus reduces the use of debt (Frank and Goyal, Frank and Goyal).[28] Agency costs are captured using a proxy for growth opportunities (López-Gracia and Sogorb-Mira, 2008). We include firm-specific growth expectations using the categorical variable GE, which captures expectations that are either *positive* (the firm expects its sales to increase in the next one to three years), *neutral* (sales is expected to remain unchanged) or *negative* (sales is expected to decline). Firms with more growth opportunities are expected to require less debt (Fama and French, 2002). We further control for the planned size of the investment project (divided by total assets) INV; for firm size, TA, defined as the natural logarithm of total assets, and for the age of the firm, AGE, defined as the natural logarithm of the number of years the firm has been operating. The variables LEV, $NTDS$, FA and TA are lagged by one period in order to mitigate the possibility of simultaneity. We also include industry-year fixed effects, $\lambda_{j,t}$, to control for macroeconomic shocks at the industry level. The definitions of variables and the summary statistics are shown in Table B.3 and Table B.4 in Appendix B.1.

In the second step, we test for the existence of an income effect by analysing how the reduction in interest rates affects the availability of internal funds, approximated by the cash flow to total asset ratio. Following the credit channel literature, we

[26] The term 'tax shield' refers to reductions in taxable income through claiming allowable deductions, such as depreciation and interest payments on certain debts. These deductions 'shield' parts of firms' taxable income from taxation. In general interest expenses are referred to as *debt tax shields* (Vanacker and Manigart, 2010).

[27] The Creditreform Creditworthiness Indicator is calculated from information about the firm's liquidity, profit and asset position. It also takes into account structural risks such as firm size and legal form as well as sectoral risks (Creditreform, 2015).

[28] Fixed tangible assets are easier to collateralize and are expected to suffer smaller losses of value if the firm goes into financial distress (Frank and Goyal, Frank and Goyal).

use a dummy variable, INT_t, that indicates years in which nominal interest rates declined in order to capture the effect (e.g. Oliner and Rudebusch, 1996a).[29] As the main target of our analysis is the immediate decision about credit application by SMEs, we base INT_t on the borrowing costs of NFCs. Hence, it takes the value of 1 if borrowing costs declined in year t and 0 otherwise.[30] We estimate in our second step the following model:

$$CF_{i,t} = \beta_0 + \beta_1 INT_t + \beta_2 X_{i,t} + \lambda_{j,t} + \epsilon_{i,t} \tag{3.9}$$

In accordance with hypothesis (2) we expect the coefficient of INT_t to be positive. That is, years during which borrowing costs declined are associated with a higher cash flow to total asset ratio. $X_{i,t}$ is a vector comprising firm-specific control variables that represent potential drivers of a firm's cash flow. This includes sales growth, $GROWTH$, which we expect to have a positive impact on CF; the debt to total assets ratio, LEV (lagged by one period), which we expected to have a negative impact (due to higher interest expenses associated with higher debt levels); and the firm's creditworthiness, CW. Furthermore, we control for firm size and age by including TA (lagged by one period) and AGE.

If internal funds have a significant negative effect on SMEs' decision to use bank debt, as tested in step one, and a reduction in interest rates has a significant positive effect on internal funds, as tested in step two, the validity of the income effect can be deduced. A reduction in interest rates in period $t-1$ would then lead to an increase of internal funds in period $t-1$, which would reduce the loan application probability and the desired share of bank loans in period t.

In the third step we test whether a decline in interest rates provides an incentive for firms to substitute internal financing with bank debt financing (substitution effect). To do so we interact the dummy variable INT_t with the variable measuring the availability of internal funds $CF_{i,t-1}$:

[29] Alternatively, a set of annual macro-level data, including interest rate data, could be included in the estimation (e.g. Jiménez et al., 2012). However, this requires the macro variables to be uncorrelated. This assumption is not always upheld and the approach can additionally suffer from an omitted variable bias. We estimate a model including macro variables as a robustness check (see Appendix B.3).

[30] Between 2005 and 2014, borrowing costs declined in six years (2005, 2009, 2010, and 2012-2014) and increased in four years (2006-2008 and 2011). Data on borrowing costs are provided by the ECB.

$$APPLY_{i,t} = \beta_0 + \beta_1 CF_{i,t-1} + \beta_2 (INT_t{}^*CF_{i,t-1}) + \beta_3 Y_{i,t} + \lambda_{j,t} + \epsilon_{i,t} \quad (3.10)$$

$$SHARE_{i,t} = \beta_0 + \beta_1 CF_{i,t-1} + \beta_2 (INT_t{}^*CF_{i,t-1}) + \beta_3 Y_{i,t} + \lambda_{j,t} + \epsilon_{i,t} \quad (3.11)$$

If a reduction in interest rates alters firms to replace internal funds with bank debt, we expect the coefficient β_2 to be positive. This would indicate that during periods of interest rate reduction, SMEs would rely less on internal funds to finance their investment projects and would instead turn more quickly to bank loan financing.

To exploit the panel nature of our data and to control for unobserved time-invariant heterogeneity at the firm level, we estimate models (3.7) to (3.11) using linear fixed-effects models.[31] As $APPLY$ is a binary variable and $SHARE$ a fractional response variable confined to the]0,1] interval, the use of non-linear models to estimate equations (3.7), (3.8), (3.10) and (3.11) would be preferable to a linear model. For the case of $APPLY$ a logit model would be suitable. For the case of $SHARE$ a fractional response model, as proposed by Papke and Wooldridge (1996, 2008), and Wooldridge (2010), could be used. However, the inclusion of firm-fixed effects in a non-linear model such as logit (for the case of $APPLY$) would restrict our sample to only those firms that had applied at least one time for a bank loan and one time not. This could cause a selection problem. Furthermore, Jiménez et al. (2012) point out that the main advantage of using linear instead of non-linear models is the intuitive interpretation of the interaction term coefficients in linear models. Moreover, Ai and Norton (2003) and Norton et al. (2004) show that in non-linear models the ordinarily reported standard errors and marginal effects of interaction terms would require corrections. Owing to these potential shortcomings we follow Jiménez et al. (2012) and use linear models in our analysis. We study non-linear models as a robustness check (see Appendix B.3).

To test whether firms of varying sizes react differently, we additionally estimate each model for different size classes: micro firms (up to 9 full-time employees), small firms (between 10 and 49 full-time employees), and medium-sized firms (50 or more full-time employees).

[31] Results from a Hausman test and an F-test, respectively, suggest that a panel fixed-effects model is to be preferred to both a random-effects panel model and a pooled ordinary least squares model.

3.4.3 Estimation Results

Step 1: Internal funds and SMEs' financing decisions

Table 3.1 and Table 3.2 report the results of our first step, which tests the validity of the POT for the loan application probability and the desired loan share, respectively. The first columns show the results for the total sample. In accordance with the POT, we find that internal funds (proxied by the cash flow to total asset ratio) have a negative impact on the loan application probability and the desired bank loan share. However, the effect is statistically significant only for the desired bank loan share. Our estimation results thus only partly confirm the validity of the POT.

The results show that an increase of one standard deviation (SD) in the cash flow to total assets ratio – which equates to 13 percentage points – reduces the desired bank loan share in the financing mix of an investment project by around 1.5 percentage points.[32] The effect size, however, varies considerably by firm size (Table 3.2, columns 2-4). The effect is largest for micro firms, with 1 SD increase in the cash flow ratio being associated with a decline of 3.6 percentage points in the desired bank loan share. For medium-sized firms, the effect amounts to a decline of 2 percentage points. For small firms, the effect is not statistically significant.

In addition to internal funds, the planned size of the investment project has a significant effect on SMEs' decisions to use bank debt. However, the effect differs for loan application probability versus desired loan share. The positive coefficient in the loan application model (Table 3.1) indicates that larger investment projects increase the need for external finance, raising the odds that a firm will apply for a bank loan. This finding is in line with the POT. By contrast, the negative coefficient in the desired loan share model (Table 3.2) indicates that – given the firm has applied for a loan – the larger the project, the smaller the desired loan share. This could be an indication of SMEs' limited access to high-volume loans, such that SMEs have to additionally look for alternative external funds to finance their large-scale investment projects.[33]

[32] Estimated by 0.13*(-0.1126)=-0.014638.

[33] Analysing the firm-specific *realized* financing mix that is also available in our dataset, we find that the share of subsidized funds (e.g. subsidized loans) considerably increases with increasing size of the investment project, crowding out 'normal' bank loans.

Table 3.1: Results Step 1 - Loan Application Probability

$APPLY_{i,t}$	(1) Total Sample	(2) Micro Firms	(3) Small Firms	(4) Medium Firms
$CF_{i,t-1}$	-0.0178	0.0206	-0.0894	-0.0065
	[0.0414]	[0.0874]	[0.0761]	[0.0599]
$LEV_{i,t-1}$	-0.0444	-0.1617*	0.0265	-0.0318
	[0.0356]	[0.0829]	[0.0595]	[0.0598]
$NTDS_{i,t-1}$	-0.0649	0.1061	0.1504	-0.2015
	[0.1003]	[0.2157]	[0.1621]	[0.1344]
$CW_{i,t}$	-0.0004*	-0.0006	-0.0005	0.0000
	[0.0002]	[0.0004]	[0.0003]	[0.0004]
$FA_{i,t-1}$	0.0002	0.0008	-0.0002	0.0000
	[0.0004]	[0.0010]	[0.0006]	[0.0007]
$GE\_neutral_{i,t}$	0.0104	-0.0158	0.0157	0.0199
	[0.0113]	[0.0339]	[0.0179]	[0.0174]
$GE\_positive_{i,t}$	0.0337***	-0.0017	0.0208	0.0541***
	[0.0122]	[0.0393]	[0.0198]	[0.0186]
$INV_{i,t}$	1.1902***	0.9154***	1.2307***	1.2940***
	[0.0517]	[0.1576]	[0.0722]	[0.0891]
$TA_{i,t-1}$	-0.0145	0.0217	-0.0424*	-0.0142
	[0.0159]	[0.0536]	[0.0245]	[0.0299]
$AGE_{i,t}$	0.0468	0.3538**	0.1973**	-0.1956*
	[0.0541]	[0.1527]	[0.0773]	[0.1003]
Constant	0.4929*	-0.9329	0.2576	1.2552**
	[0.2842]	[0.7986]	[0.4092]	[0.5664]
Observations	18,090	2,579	7,765	7,349

Notes: $APPLY$ is the dependent variable. All models estimated using a fixed-effects linear probability model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of industry-year fixed effects. Definition of size classes: micro firms ($\leq$ 9 FTEs), small firms (10-49 FTEs) and medium-sized firms ($\geq$ 50 FTEs). Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

The results for the remaining control variables are inconclusive, with coefficients and levels of significance differing depending on the model and the subsample. We find a statistically significant negative relationship between SMEs' desired bank loan share and fixed assets, which contradicts our assumptions. Furthermore, the size of the firm, is inversely related with the desired loan share of micro firms. We also find a statistically significant positive relationship between the age of the firm and the loan application probability of micro and small firms but a negative relationship for medium-sized firms.

Table 3.2: Results Step 1 - Desired Bank Loan Share

$SHARE_{i,t}$	(1) Total Sample	(2) Micro Firms	(3) Small Firms	(4) Medium Firms
$CF_{i,t-1}$	-0.1126***	-0.2767***	-0.0507	-0.1530***
	[0.0380]	[0.0904]	[0.1099]	[0.0538]
$LEV_{i,t-1}$	-0.0525	-0.0259	-0.0595	-0.0639
	[0.0407]	[0.1069]	[0.0732]	[0.0626]
$NTDS_{i,t-1}$	0.0479	-0.0206	-0.0020	0.0197
	[0.0892]	[0.2099]	[0.1265]	[0.1699]
$CW_{i,t}$	0.0001	0.0011	0.0005	-0.0004
	[0.0003]	[0.0008]	[0.0004]	[0.0004]
$FA_{i,t-1}$	-0.0008**	0.0008	-0.0011*	-0.0015**
	[0.0004]	[0.0013]	[0.0006]	[0.0006]
$GE\_neutral_{i,t}$	-0.0015	-0.0232	-0.0158	0.0119
	[0.0121]	[0.0459]	[0.0189]	[0.0187]
$GE\_positive_{i,t}$	0.0143	-0.0394	0.0007	0.0342*
	[0.0128]	[0.0562]	[0.0220]	[0.0183]
$INV_{i,t}$	-0.2250***	-0.2893**	-0.1894***	-0.2123***
	[0.0399]	[0.1333]	[0.0625]	[0.0649]
$TA_{i,t-1}$	-0.0432***	-0.1681**	-0.0274	-0.0377
	[0.0146]	[0.0747]	[0.0223]	[0.0240]
$AGE_{i,t}$	0.0468	0.3171	-0.0898	0.1365
	[0.0601]	[0.2199]	[0.0909]	[0.0997]
Constant	1.2541***	1.8112	1.4052***	0.9850*
	[0.2946]	[1.2162]	[0.4327]	[0.5313]
Observations	7,979	942	3,428	3,418

Notes: $SHARE$ is the dependent variable. All models estimated using a fixed-effects model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of industry-year fixed effects. Definition of size classes: micro firms ($\leq$ 9 FTEs), small firms (10-49 FTEs) and medium-sized firms ($\geq$ 50 FTEs). Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

Step 2: Income Effect

Table 3.3 shows the regression results of our second step, testing how the reduction of interest rates affects SMEs' internal funds. The results of regression model (3.9) show that the coefficient of the dummy variable INT_t is positive and statistically different from zero. Hence, a reduction of borrowing costs in period t increases the cash flow ratio in period t. These findings are in accordance with hypothesis (2) and are generally consistent with the balance-sheet-channel literature. On average, a reduction in the borrowing costs for period t increases the cash flow ratio in the same period by around 5 percentage points, which is not negligible relative to the cash flow ratio sample average of 15 percent.

Table 3.3: Results Step 2 - Income Effect

$CF_{i,t}$	(1) Total Sample	(2) Micro Firms	(3) Small Firms	(4) Medium Firms
INT_t	0.0494***	0.1144**	-0.0023	0.0748***
	[0.0168]	[0.0544]	[0.0382]	[0.0186]
$GROWTH_{i,t}$	-0.0000	0.0088	-0.0000	-0.0002
	[0.0001]	[0.0057]	[0.0000]	[0.0001]
$LEV_{i,t-1}$	0.0232**	0.0201	0.0311**	0.0235*
	[0.0099]	[0.0336]	[0.0143]	[0.0135]
$CW_{i,t}$	0.0001	0.0001	0.0000	0.0000
	[0.0001]	[0.0002]	[0.0001]	[0.0001]
$TA_{i,t-1}$	-0.0243***	-0.0230	-0.0233***	-0.0241***
	[0.0039]	[0.0166]	[0.0054]	[0.0064]
$AGE_{i,t}$	0.0150	0.0560	0.0094	-0.0105
	[0.0125]	[0.0414]	[0.0188]	[0.0201]
Constant	0.3952***	0.2231	0.3842***	0.4947***
	[0.0670]	[0.2611]	[0.0941]	[0.1200]
Observations	18,935	2,671	8,138	7,710

Notes: CF is the dependent variable. All models estimated using a fixed-effects model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of industry-year fixed effects. Definition of size classes: micro firms ($\leq$ 9 FTEs), small firms (10-49 FTEs) and medium-sized firms ($\geq$ 50 FTEs). Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

However, a statistically significant effect is not observed for small firms. For the other size classes we find that a reduction in borrowing costs increases the cash flow ratio of micro firms by 11.4 percentage points, and of medium sized firms by 7.5 percentage points. For the control variables, we find that only firms' leverage and size have statistically significant effects on the cash flow ratio. Contrary to our assumptions, a higher leverage ratio is positively related to cash flow in our estimation model. Furthermore, a larger firm size is associated with a lower cash flow ratio.

Summing up the results of steps one and two, we find evidence for the presence of an income effect of borrowing-cost reductions on SMEs' decisions to use bank debt. Declining borrowing costs non-negligibly increase SMEs' internal financing capacity, which subsequently reduces their desired bank loan share in the following year.

Step 3: Substitution Effect

To test whether the reduction in interest rates alters SMEs' preference order, we interact the dummy variable INT_t, which indicates whether borrowing costs declined, with firms' cash flow ratio $CF_{i,t-1}$. Table 3.4 and Table 3.5 show the results for the loan application and loan share models, respectively. For brevity, we report and discuss only the coefficients of interest.[34] In our estimation model the coefficient of $CF_{i,t-1}$ reflects the effect of internal funds on the loan application probability and the desired bank loan share, in years of nondecreasing borrowing costs. The coefficient of the interaction term $CF_{i,t-1}*INT_{i,t}$ reflects the difference compared with years in which borrowing costs declined.[35] A positive coefficient of the interaction term would indicate that the negative effect of internal funds on both dependent variables decreases when borrowing costs decline.

Table 3.4: Results Step 3 - Loan Application Probability

$APPLY_{i,t}$	(1) Total Sample	(2) Micro Firms	(3) Small Firms	(4) Medium Firms
(1) $CF_{i,t-1}$	-0.0384	0.0289	-0.1544*	0.0248
	[0.0481]	[0.0934]	[0.0849]	[0.0793]
(2) $CF_{i,t-1}*INT_t$	0.0338	-0.0159	0.1141	-0.0533
	[0.0493]	[0.0957]	[0.0863]	[0.0832]
Observations	18,090	2,579	7,765	7,349

Notes: $APPLY$ is the dependent variable. All models estimated using a fixed-effects model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of industry-year fixed effects. Definition of size classes: micro firms (≤ 9 FTEs), small firms (10-49 FTEs) and medium-sized firms (≥ 50 FTE). Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

Table 3.5: Results Step 3 - Desired Bank Loan Share

$SHARE_{i,t}$	(1) Total Sample	(2) Micro Firms	(3) Small Firms	(4) Medium Firms
(1) $CF_{i,t-1}$	-0.1535***	-0.2226**	-0.0949	-0.2012***
	[0.0546]	[0.1084]	[0.1271]	[0.0770]
(2) $CF_{i,t-1}*INT_t$	0.0617	-0.1257	0.0662	0.0838
	[0.0597]	[0.1466]	[0.1001]	[0.1021]
Observations	7,979	942	3,428	3,418

Notes: $SHARE$ is the dependent variable. All models estimated using a fixed-effects model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of industry-year fixed effects. Definition of size classes: micro firms (≤ 9 FTEs), small firms (10-49 FTEs) and medium-sized firms (≥ 50 FTE). Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

For the loan application probability (Table 3.4), the coefficient of the interaction term shows the expected positive sign only for the subsample of small firms, yet it is

[34] The complete estimation results are shown in Appendix B.2.

[35] The sum of both coefficients would reflect the effect of internal funds on both dependent variables in years of declining borrowing costs.

statistically not significant. However, in contrast to our baseline model in step one, the coefficient of the cash flow ratio is statistically significant for small firms, such that – in line with the POT – a higher cash flow ratio reduces the probability of applying for a bank loan. For the desired loan share model (Table 3.5), the interaction of cash flow with the borrowing cost reduction dummy variable shows the expected positive sign only for the subsample of small and medium-sized firms. However, the effect is statistically not significant. In other words, the negative effect of internal funds on the desired loan share does not differ between periods of increasing and decreasing borrowing costs.

Summing up the results for step three, we cannot confirm a statistically significant substitution effect of declining borrowing costs for German SMEs in the period 2005 to 2014. Hence, SMEs did not increase their preference for bank loans in the observation period. This finding generally parallels those of the previous section which showed a decline in bank borrowing by German NFCs.

The results of our empirical analysis are robust with regard to alternative estimation methods. Using fixed-effects logit models for $APPLY$ and fractional logit models for $SHARE$ as a robustness check, our estimation results vary only slightly in terms of the coefficient sign and significance, without changing the general findings (Table B.8 to B.11 in Appendix B.3). Furthermore, replacing the borrowing cost dummy variable in model (3.9) by a set of macro variables confirms the findings that a drop in borrowing cost strengthens firms' internal financing capacity (Table B.12).

3.5 Conclusion

High private sector debt can have long-lasting negative impacts on the economy. It is therefore crucial to understand the drivers of corporate sector debt financing. The aim of this study is to analyse how the reduction in interest rates affects German SMEs' financing decisions, in particular their willingness to use bank loans to finance investment projects. Assuming SMEs follow a preference order when making financing decisions, and assuming too that SMEs depend on bank debt if they require external finance for investment projects, we theoretically derive several (partly opposing) effects of interest rate reductions: an encouragement effect, an income and a substitution effect.

Analysing aggregate data for the period 2003 to 2015, we find that in periods of declining interest rates, the outstanding amounts of bank debt in Germany, as well as the *realized* share of bank loans in SMEs' financing mix, declined rather than increased. These findings suggest a predominant income effect. Our firm-level analysis of SMEs' *desired* bank loan share confirms these findings and disconfirms a substitution effect in the period 2005 to 2014. Hence, the interest rate decline caused by the ECB's expansionary monetary policy has not induced German SMEs to replace internal funds with bank debt, but has rather strengthened their internal financing capacity, thus reducing their demand for bank loans.

Our findings of a predominant income effect of declining interest rates highlight the importance of the interest rate environment for firms' financing behaviour and bank loan demand. This has important policy implications. Firstly, our results confirm that a low-interest rate policy works as a kind of subsidy to the corporate sector, by significantly affecting firms' interest expenses and cash flow. Secondly, in times of low corporate sector demand for external finance (due to low investment activities), declining interest rates can further suppress corporate sector borrowing. On the one hand, this reduces the danger of accelerating corporate debt levels – as experienced prior to the crisis in several countries. On the other hand, low corporate sector demand for bank loans has a substantial effect on the banking sector, by depressing financial intermediaries' traditional sources of income.

Future research on the impact of interest rates on corporate sector bank loan demand should be conducted. Specific focus points should include variations in the effect sizes of income and substitution effects associated with interest rate changes, given different states of the economy and phases of the business cycle.[36] This can help to derive in what circumstances a reduction of interest rates leads to an increase or decrease in firms' use of bank debt.

[36] The non-existence of a substitution effect in this period might reflect unique circumstances of German SMEs that resulted in a cautious use of bank debt. Research on possible substitution effects of interest rate reductions should therefore be extended to other countries that experienced strong increases in corporate sector debt (e.g. Spain).

Appendix B

B.1 Sample Structure and Variable Definition

Table B.1: Number of Observations by Year

Year	Observations
2005	1,404
2006	1,723
2007	1,881
2008	2,526
2009	2,286
2010	2,195
2011	1,940
2012	1,576
2013	1,605
2014	954
Total	18,090

Table B.2: Number of Firms by Sector

Sector	No. of Firms
Accommodation	144
Agriculture	126
Construction	1,274
Energy and Water	108
Financial Services	14
Information	141
Manufacturing	2,597
Mining	5
PA, Education, Healthcare	151
Real Estate	135
Trade	2,299
Transportation	432
Technical Services	516
Other Services	330

Table B.3: Variable Definition

Dependent Variable	
SHARE	Desired share of bank loans in financing mix (excluding zeros)
APPLY	1: Firm applied for a bank loan to finance investment project 0: Otherwise
Explanatory Variables	
CF	Cash flow (net income + depreciation) over total assets
INT	1: Borrowing costs for non-financial corporations declined 0: Otherwise
TA	Natural log of total assets
AGE	Natural log of one plus age of firm
INV	Planned investment volume over total assets
CW	Creditreform Creditworthiness Indicator
FA	Fixed assets over total assets
LEV	Debt over total assets
GE	Growth expectations _negative - Sales will decline _neutral - Sales remains the same _positive - Sales will increase

Table B.4: Descriptive Statistics

	Mean	SD	Min	Max
SHARE	0.68	0.27	0.05	1.00
APPLY	0.44	0.50	0.00	1.00
Explanatory Variables:				
CF	0.15	0.13	-0.31	1.30
INT	0.55	0.50	0.00	1.00
INV	0.12	0.13	0.00	1.43
TA	9,028	17,671	40	173112
AGE	41.45	41.51	2	660
CW	228.11	45.26	100	600
FA	33.94	24.41	0.00	96.77
LEV	0.74	0.22	0.08	1.59
GE_negative	0.24	0.43	0.00	1.00
GE_neutral	0.33	0.47	0.00	1.00
GE_positive	0.44	0.50	0.00	1.00

Notes: TA in 1000EUR. AGE in levels.

B.2 Complete Results

Table B.5: Complete Results Step 3 - Loan Application Probability

$APPLY_{i,t}$	(1) Total Sample	(2) Micro Firms	(3) Small Firms	(4) Medium Firms
$CF_{i,t-1}$	-0.0384	0.0289	-0.1544*	0.0248
	[0.0481]	[0.0934]	[0.0849]	[0.0793]
$CF_{i,t-1}*INT_{i,t}$	0.0338	-0.0159	0.1141	-0.0533
	[0.0493]	[0.0957]	[0.0863]	[0.0832]
$LEV_{i,t-1}$	-0.0440	-0.1619*	0.0295	-0.0327
	[0.0356]	[0.0830]	[0.0594]	[0.0599]
$NTDS_{i,t-1}$	-0.0670	0.1032	0.1277	-0.1993
	[0.0991]	[0.2172]	[0.1576]	[0.1366]
$CW_{i,t}$	-0.0004*	-0.0006	-0.0005	0.0000
	[0.0002]	[0.0004]	[0.0003]	[0.0004]
$FA_{i,t-1}$	0.0002	0.0008	-0.0002	0.0000
	[0.0004]	[0.0010]	[0.0006]	[0.0007]
$GE\_neutral_{i,t}$	0.0104	-0.0159	0.0155	0.0197
	[0.0113]	[0.0339]	[0.0180]	[0.0174]
$GE\_positive_{i,t}$	0.0338***	-0.0017	0.0205	0.0538***
	[0.0122]	[0.0393]	[0.0197]	[0.0186]
$INV_{i,t}$	1.1906***	0.9152***	1.2317***	1.2934***
	[0.0518]	[0.1576]	[0.0722]	[0.0891]
$TA_{i,t-1}$	-0.0147	0.0217	-0.0423*	-0.0137
	[0.0159]	[0.0536]	[0.0246]	[0.0299]
$AGE_{i,t}$	0.0466	0.3530**	0.1956**	-0.1949*
	[0.0541]	[0.1529]	[0.0773]	[0.1004]
Constant	0.4926*	-0.9587	0.2423	1.2478**
	[0.2842]	[0.7993]	[0.4099]	[0.5667]
Observations	18,090	2,579	7,765	7,349

Notes: *APPLY* is the dependent variable. All models estimated using a fixed-effects linear probability model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Definition of size classes: micro firms ($\leq$ 9 FTEs), small firms (10-49 FTEs) and medium-sized firms ($\geq$ 50 FTEs). Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

Table B.6: Complete Results Step 3 - Desired Bank Loan Share

$SHARE_{i,t}$	(1) Total Sample	(2) Micro Firms	(3) Small Firms	(4) Medium Firms
$CF_{i,t-1}$	-0.1535***	-0.2226**	-0.0949	-0.2012***
	[0.0546]	[0.1084]	[0.1271]	[0.0770]
$CF_{i,t-1}*INT_t$	0.0617	-0.1257	0.0662	0.0838
	[0.0597]	[0.1466]	[0.1001]	[0.1021]
$LEV_{i,t-1}$	-0.0524	-0.0265	-0.0599	-0.0617
	[0.0407]	[0.1068]	[0.0732]	[0.0627]
$NTDS_{i,t-1}$	0.0426	-0.0440	-0.0120	0.0041
	[0.0851]	[0.2194]	[0.1294]	[0.1604]
$CW_{i,t}$	0.0001	0.0010	0.0005	-0.0004
	[0.0003]	[0.0008]	[0.0004]	[0.0004]
$FA_{i,t-1}$	-0.0009**	0.0008	-0.0011*	-0.0015**
	[0.0004]	[0.0013]	[0.0006]	[0.0006]
$GE\_neutral_{i,t}$	-0.0017	-0.0185	-0.0162	0.0121
	[0.0122]	[0.0460]	[0.0189]	[0.0188]
$GE\_positive_{i,t}$	0.0142	-0.0356	0.0005	0.0344*
	[0.0128]	[0.0561]	[0.0220]	[0.0183]
$INV_{i,t}$	-0.2233***	-0.2960**	-0.1881***	-0.2100***
	[0.0398]	[0.1337]	[0.0624]	[0.0645]
$TA_{i,t-1}$	-0.0440***	-0.1665**	-0.0280	-0.0395
	[0.0146]	[0.0748]	[0.0223]	[0.0243]
$AGE_{i,t}$	0.0469	0.3123	-0.0912	0.1372
	[0.0602]	[0.2192]	[0.0913]	[0.0998]
Constant	1.2619***	1.8974	1.4127***	1.0062*
	[0.2946]	[1.2084]	[0.4329]	[0.5326]
Observations	7,979	942	3,428	3,418

Notes: *SHARE* is the dependent variable. All models estimated using a fixed-effects model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Definition of size classes: micro firms ($\leq$ 9 FTEs), small firms (10-49 FTEs) and medium-sized firms ($\geq$ 50 FTEs). Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

B.3 Robustness Checks

Sample Selection

To rule out a selection bias we estimate a selection model following a two-step procedure proposed by Wooldridge (1995). We first estimate year-by-year reduced form probit models for the decision variable $APPLY$:

$$APPLY_{i,t} = \beta_0 + \beta_1 Z_{i,t} + \epsilon_{i,t} \tag{B.1}$$

Except for the explanatory variables that we include in model (3.7) we additionally include in the selection equation a categorical variable capturing the degree of urbanization of the firm's headquarters location: (1) city, (2) region with low degree of urbanization and (3) rural area. As the density of bank branches is lower in rural areas bank loan applications are expected to be higher for firm's in these areas, as the application costs would be lower. As was shown in equation (3.5) higher application costs lower the probability of applying for a bank loan.

Based on the results of the probit models we construct for each period the selection term – that is, the inverse mills ratio $\lambda_{i,t}$:

$$\lambda_{i,t} = \frac{\phi(Z'\hat{\beta})}{\Phi(Z'\hat{\beta})} \tag{B.2}$$

Next, we include $\lambda_{i,t}$ in our estimation equation (3.8) to correct for sample selection. The results are shown in Table B.7. Column (1) reports the results for the loan share model including the correction term. For comparison, column (2) reports the results for the baseline model. The correction term $\lambda_{i,t}$ is found to be statistically not significant. In addition, the estimation results of both models are fairly similar. Hence, we conclude that sample selection does not seem to be a problem.

Non-Linear Models

Table B.8 and B.9 show the estimation results for the loan application probability model using a fixed-effects logit model. The coefficient of the cash flow to total asset ratio remains negative. In contrast to the results of the linear fixe-effects model the coefficient becomes statistically significant at the 5-percent level for the subgroup of small firms. The coefficients from the interaction term remain statistically not significant.

Table B.10 and B.11 show the estimation results of the loan share model using a fractional logit model that is based on Papke and Wooldridge (2008) and Wooldridge (2010).[37] The coefficient of the cash flow to total asset ratio remains negative for the total sample and the subgroups of micro and medium-sized firms. It is statistically significant only for the total sample and the subgroup of medium-sized firms. The coefficients of the interaction term remain statistically not significant.

Macro Variables

To test the robustness of our results for step two we estimate a variation of model (3.9) including a set of macroeconomic control variables:

$$CF_{i,t} = \beta_0 + \beta_1 BCOST_t + \beta_2 \Delta GDP_t + \beta_3 INF_t + \beta_4 X_{i,t} + \lambda_{j,t} + \epsilon_{i,t} \tag{B.3}$$

with $BCOST_t$ being the borrowing costs for NFCs in Germany (in levels) in year t, ΔGDP_t is the growth rate of the real gross domestic product, and INF_t is the inflation rate. All other variables are included as defined above.

The estimation results of model (B.3) are shown in Table B.12. The coefficient of the cost of borrowing indicator is negative and statistically significant for the total sample and the subgroup of medium-sized firms. This implies that higher borrowing costs are associated with a decline in the cash flow ratio. Our results hence confirm that declining interest rates strengthen a firm's internal financing capacity. We also find that higher real GDP growth is linked to a higher cash flow ratio.

[37] We use the *fracreg* command of *STATA 14*.

Table B.7: Robustness Check - Sample Selection Model

$SHARE_{i,t}$	(1) Selection Correction	(2) No Selection Correction
$\lambda_{i,t}$	0.0611	
	[0.0397]	
$CF_{i,t-1}$	-0.1379***	-0.1126***
	[0.0410]	[0.0380]
$LEV_{i,t-1}$	-0.0280	-0.0525
	[0.0429]	[0.0407]
$NTDS_{i,t-1}$	0.0751	0.0479
	[0.0946]	[0.0892]
$CW_{i,t}$	0.0001	0.0001
	[0.0003]	[0.0003]
$FA_{i,t-1}$	-0.0006	-0.0008**
	[0.0004]	[0.0004]
$GE\_neutral_{i,t}$	0.0030	-0.0015
	[0.0122]	[0.0121]
$GE\_positive_{i,t}$	0.0191	0.0143
	[0.0132]	[0.0128]
$INV_{i,t}$	-0.1148	-0.2250***
	[0.0814]	[0.0399]
$TA_{i,t-1}$	-0.0389***	-0.0432***
	[0.0148]	[0.0146]
$AGE_{i,t}$	0.0636	0.0468
	[0.0596]	[0.0601]
Constant	1.0650***	1.2541***
	[0.3120]	[0.2946]
Observations	7,979	7,979

Notes: $SHARE$ is the dependent variable. Both models estimated using a fixed-effects model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

Table B.8: Robustness Check - Logit Model (1)

$APPLY_{i,t}$	(1) Total Sample	(2) Micro Firms	(3) Small Firms	(4) Medium Firms
$CF_{i,t-1}$	-0.5235	-0.6323	-0.9940*	-0.4629
	[0.3649]	[0.9502]	[0.5675]	[0.6555]
$LEV_{i,t-1}$	-0.4055	-1.7580**	-0.0010	-0.1968
	[0.2673]	[0.8159]	[0.4267]	[0.4470]
$NTDS_{i,t-1}$	0.2706	0.1716	1.2595	-2.4947
	[0.8495]	[3.8497]	[1.1783]	[2.5337]
$CW_{i,t}$	-0.0026*	-0.0080	-0.0032	0.0000
	[0.0016]	[0.0050]	[0.0024]	[0.0027]
$FA_{i,t-1}$	0.0007	0.0089	-0.0034	0.0013
	[0.0027]	[0.0072]	[0.0040]	[0.0050]
$GE\_neutral_{i,t}$	0.0693	-0.1869	0.1177	0.1618
	[0.0827]	[0.2674]	[0.1300]	[0.1331]
$GE\_positive_{i,t}$	0.2214**	0.1330	0.0841	0.3852***
	[0.0876]	[0.3067]	[0.1411]	[0.1353]
$INV_{i,t}$	10.1096***	7.2238***	10.9304***	11.7953***
	[0.4501]	[1.0344]	[0.7388]	[0.8102]
$TA_{i,t-1}$	-0.1321	0.0971	-0.4170**	-0.1359
	[0.1144]	[0.3841]	[0.1814]	[0.2099]
$AGE_{i,t}$	0.1618	2.7670**	1.4536**	-2.0313***
	[0.3750]	[1.2607]	[0.6076]	[0.7214]
Observations	7,456	663	2,998	3167

Notes: $APPLY$ is the dependent variable. All models estimated using a fixed-effects logit model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of year fixed effects. Definition of size classes: micro firms ($\leq$ 9 FTEs), small firms (10-49 FTEs) and medium-sized firms ($\geq$ 50 FTEs). Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

Table B.9: Robustness Check - Logit Model (2)

$APPLY_{i,t}$	(1) Total Sample	(2) Micro Firms	(3) Small Firms	(4) Medium Firms
$CF_{i,t-1}$	-0.7811*	-0.3928	-1.8968**	-0.0728
	[0.4717]	[1.1793]	[0.8065]	[0.7990]
$CF_{i,t-1}{*}INT_t$	0.3950	-0.4203	1.1910	-0.8414
	[0.4670]	[1.1830]	[0.7508]	[0.8773]
$LEV_{i,t-1}$	-0.3979	-1.7628**	0.0271	-0.2208
	[0.2673]	[0.8160]	[0.4274]	[0.4486]
$NTDS_{i,t-1}$	0.1957	0.1573	1.1779	-2.4468
	[0.8535]	[3.8576]	[1.2448]	[2.5937]
$CW_{i,t}$	-0.0026*	-0.0083	-0.0033	0.0000
	[0.0016]	[0.0051]	[0.0024]	[0.0027]
$FA_{i,t-1}$	0.0008	0.0088	-0.0034	0.0013
	[0.0027]	[0.0072]	[0.0040]	[0.0050]
$GE\_neutral_{i,t}$	0.0710	-0.1849	0.1234	0.1550
	[0.0827]	[0.2677]	[0.1302]	[0.1334]
$GE\_positive_{i,t}$	0.2212**	0.1373	0.0763	0.3780***
	[0.0876]	[0.3069]	[0.1414]	[0.1356]
$INV_{i,t}$	10.1208***	7.2196***	10.9788***	11.7958***
	[0.4506]	[1.0342]	[0.7413]	[0.8100]
$TA_{i,t-1}$	-0.1370	0.1025	-0.4279**	-0.1320
	[0.1147]	[0.3838]	[0.1825]	[0.2104]
$AGE_{i,t}$	0.1602	2.7306**	1.4453**	-2.0183***
	[0.3751]	[1.2656]	[0.6073]	[0.7205]
Observations	7,456	663	2,998	3,167

Notes: $APPLY$ is the dependent variable. All models estimated using a fixed effects logit model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of year fixed effects. Definition of size classes: micro firms ($\leq$ 9 FTEs), small firms (10-49 FTEs) and medium-sized firms ($\geq$ 50 FTEs). Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

Table B.10: Robustness Check - Fractional Response Model (1)

$SHARE_{i,t}$	(1) Total Sample	(2) Micro Firms	(3) Small Firms	(4) Medium Firms
$CF_{i,t-1}$	-0.2199**	0.2085	-0.2018	-0.5408***
	[0.1066]	[0.2193]	[0.1648]	[0.1942]
$LEV_{i,t-1}$	0.6209***	0.5314***	0.6829***	0.5635***
	[0.0692]	[0.1801]	[0.1086]	[0.1077]
$NTDS_{i,t-1}$	0.4118*	0.4784	1.0784**	0.5168
	[0.2422]	[0.7588]	[0.4368]	[0.3196]
$CW_{i,t}$	0.0002	-0.0001	0.0002	0.0004
	[0.0003]	[0.0011]	[0.0005]	[0.0005]
$FA_{i,t-1}$	-0.0028***	-0.0034*	-0.0036***	-0.0033***
	[0.0006]	[0.0018]	[0.0010]	[0.0010]
$GE\_neutral_{i,t}$	0.0187	0.0791	-0.0870	0.0694
	[0.0390]	[0.1229]	[0.0600]	[0.0587]
$GE\_positive_{i,t}$	0.1020***	0.0289	0.0216	0.1855***
	[0.0379]	[0.1223]	[0.0592]	[0.0563]
$INV_{i,t}$	-0.8632***	-1.3960***	-0.8561***	-0.6228***
	[0.0992]	[0.2446]	[0.1420]	[0.1734]
$TA_{i,t-1}$	-0.1629***	-0.1083**	-0.1628***	-0.1063***
	[0.0112]	[0.0491]	[0.0210]	[0.0215]
$AGE_{i,t}$	0.0233	-0.0482	0.0363	0.0356
	[0.0162]	[0.0547]	[0.0253]	[0.0235]
Constant	2.6447***	2.0579**	2.5939***	1.6894***
	[0.2400]	[0.8306]	[0.4008]	[0.4249]
Observations	8,153	971	3,519	3,468

Notes: $SHARE$ is the dependent variable. All models estimated using a fractional logit model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of industry-year fixed effects. Definition of size classes: micro firms ($\leq$ 9 FTEs), small firms (10-49 FTEs) and medium-sized firms ($\geq$ 50 FTEs). Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

Table B.11: Robustness Check - Fractional Response Model (2)

$SHARE_{i,t}$	(1) Total Sample	(2) Micro Firms	(3) Small Firms	(4) Medium Firms
$CF_{i,t-1}$	-0.1837	0.5231	-0.4234*	-0.5932**
	[0.1586]	[0.3440]	[0.2446]	[0.2567]
$CF_{i,t-1}*INT_t$	-0.0579	-0.4955	0.3536	0.0941
	[0.1847]	[0.4055]	[0.2804]	[0.3237]
$LEV_{i,t-1}$	0.6210***	0.5300***	0.6843***	0.5630***
	[0.0692]	[0.1803]	[0.1088]	[0.1077]
$NTDS_{i,t-1}$	0.4166*	0.4618	1.1212**	0.4909
	[0.2420]	[0.7365]	[0.4454]	[0.3342]
$CW_{i,t}$	0.0002	-0.0000	0.0002	0.0004
	[0.0003]	[0.0011]	[0.0005]	[0.0005]
$FA_{i,t-1}$	-0.0028***	-0.0033*	-0.0037***	-0.0033***
	[0.0006]	[0.0018]	[0.0010]	[0.0010]
$GE\_neutral_{i,t}$	0.0188	0.0802	-0.0869	0.0690
	[0.0390]	[0.1229]	[0.0600]	[0.0587]
$GE\_positive_{i,t}$	0.1022***	0.0369	0.0212	0.1852***
	[0.0379]	[0.1225]	[0.0592]	[0.0563]
$INV_{i,t}$	-0.8652***	-1.4275***	-0.8460***	-0.6208***
	[0.0996]	[0.2457]	[0.1424]	[0.1735]
$TA_{i,t-1}$	-0.1629***	-0.1110**	-0.1622***	-0.1064***
	[0.0112]	[0.0492]	[0.0211]	[0.0215]
$AGE_{i,t}$	0.0232	-0.0525	0.0373	0.0356
	[0.0162]	[0.0551]	[0.0253]	[0.0235]
Constant	2.6471***	2.1332**	2.5558***	1.6880***
	[0.2401]	[0.8321]	[0.4024]	[0.4247]
Observations	8,153	971	3,519	3,468

Notes: $SHARE$ is the dependent variable. All models estimated using a fractional logit model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Definition of size classes: micro firms ($\leq$ 9 FTEs), small firms (10-49 FTEs) and medium sized firms ($\geq$ 50 FTEs). Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

Table B.12: Robustness Check - Macro Variables

$CF_{i,t}$	(1) Total Sample	(2) Micro Firms	(3) Small Firms	(4) Medium Firms
$BCOST_t$	-0.0348***	0.0063	-0.0062	-0.0538***
	[0.0110]	[0.0168]	[0.0101]	[0.0148]
ΔGDP_t	0.0068*	0.0047	-0.0021	0.0119***
	[0.0037]	[0.0071]	[0.0071]	[0.0028]
INF_t	-0.0165	0.0015	0.0070	-0.0335
	[0.0219]	[0.0277]	[0.0229]	[0.0228]
$GROWTH_{i,t}$	-0.0000	0.0088	-0.0000	-0.0002
	[0.0001]	[0.0057]	[0.0000]	[0.0001]
$LEV_{i,t-1}$	0.0232**	0.0201	0.0311**	0.0235*
	[0.0099]	[0.0336]	[0.0143]	[0.0135]
$CW_{i,t}$	0.0001	0.0001	0.0000	0.0000
	[0.0001]	[0.0002]	[0.0001]	[0.0001]
$TA_{i,t-1}$	-0.0243***	-0.0230	-0.0233***	-0.0241***
	[0.0039]	[0.0166]	[0.0054]	[0.0064]
$AGE_{i,t}$	0.0150	0.0560	0.0094	-0.0105
	[0.0125]	[0.0414]	[0.0188]	[0.0201]
Constant	0.6029***	0.2806	0.3978***	0.8027***
	[0.0906]	[0.2505]	[0.0969]	[0.1219]
Observations	18,935	2,671	8,138	7,710

Notes: Dependent variable CF representing the cash flow to total asset ratio; $BCOST$ - cost of borrowing for NFCs in Germany (in levels); ΔGDP - real GDP growth; INF - inflation rate; All models estimated using a fixed-effects model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of year-industry fixed effects. Definition of size classes: micro firms ($\leq$ 9 FTEs), small firms (10-49 FTEs) and medium sized firms ($\geq$ 50 FTEs). Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

Chapter 4

Impaired Capital Reallocation in a Low-Interest Rate Environment – Evidence from German SMEs

Abstract

Post-crisis productivity growth has been exceptionally weak in many countries, including Germany. This paper presents an analysis of the impact of a prolonged period of low interest rates on the capital allocation process in a market economy. Using firm-level data of SMEs, we empirically test whether the German productivity slowdown in the post-crisis period has been caused by a less efficient allocation of capital. The results provide evidence that low-productive firms have had easier access to credit in the post-crisis period compared with the years before the crisis. This might have increased their odds of survival and lowered the incentive to increase their efficiency and productivity. The impaired reallocation and restructuring process is likely to have contributed to the low growth of productivity in Germany.

4.1 Introduction

The global financial crisis of 2008/2009 caused the most sudden and deep recession since the 1930s. Despite massive monetary policy interventions that pushed short- and long-term interest rates close to or even below zero, post-crisis GDP growth rates remain well below pre-crisis levels in most advanced economies, including Germany. Labour productivity and total factor productivity (TFP) growth in Germany and other countries has dropped to an all-time low. The global productivity slowdown has spurred a lively debate on the underlying causes and potential consequences for future output growth (Brynjolfsson and McAfee, 2011; Gordon, 2014; Andrews et al., 2015; McGowan et al., 2017).

According to Schumpeter (1942), productivity growth is closely linked to a process of 'creative destruction' and resource reallocation, as factors of production are moved from low-productive to high-productive firms (see also Foster et al., 2001). Several studies provide evidence that an impeded process of restructuring and resource reallocation has been one of the main reasons for the post-crisis productivity slowdown (e.g. Barnett et al., 2014; Gopinath et al., 2015).

In the context of Japan's weak economic performance since the 1990s, the manner in which central banks' crisis management can imped the restructuring process in the banking and corporate sector has been highlighted (Hoffmann and Schnabl, 2016). The Bank of Japan's zero-interest rate policy has been associated with a misallocation of credit towards highly indebted, unproductive and inefficient firms – so called zombie firms, thereby driving down aggregate productivity growth (Sekine et al., 2003; Peek and Rosengren, 2005; Caballero et al., 2008).

Similarly, it has been argued that the European Central Bank's (ECB) post-crisis ultra-loose monetary policy, in combination with an unstable banking sector, has impeded creative destruction and market dynamics in Europe (Forbes, 2015). Freytag and Schnabl (2017) show that monetary policy rescue measures have undermined the constitutive principles of the German social market economy. This dynamic has contributed to a decline in productivity growth.

To date there has been little empirical evidence of the connection between the low-interest rate policy, resource reallocation and the productivity slowdown in Germany. The aim of this paper is to fill this gap. By synthesising and evaluating the existing literature, we show theoretically how a prolonged period of ultra-loose monetary policy contributes to a misallocation of capital. Using firm-level data of German small and medium-sized enterprises (SMEs)[1], we empirically test whether the German productivity slowdown in the post-crisis period has been caused by inefficient allocation of capital. The findings of this paper provide insight into the long-term economic consequences of an extended period of ultra-low interest rates.

4.2 The German Productivity Puzzle

For decades – if not centuries – labour productivity and TFP in Germany and other advanced economies have risen constantly (Figure 4.1a and 4.1b). German labour productivity increased by around 168 percent between 1970 and 2016. Total factor productivity rose by around 39 percent between 1985 and 2015. Because productivity is a key source of economic growth, its increase has been accompanied by substantial improvement in the standard of living.

However, productivity growth rates have been declining since the 1980s (Table 4.1; and Figures 4.1c and 4.1d). In Germany, the annual growth rate of output per hour worked has dropped from an average of 3.8 percent in the 1970s to 2.3 percent in the 1990s, and further to 1.2 percent in the period after the financial crisis. Along with labour productivity, TFP growth rates have also declined, from an average of 1.8 percent in the 1980s to 1.2 percent for the period 2010–2015. Similar trends have been observed across all industrialized countries.[2]

Table 4.1: Productivity Growth Rates (Germany)

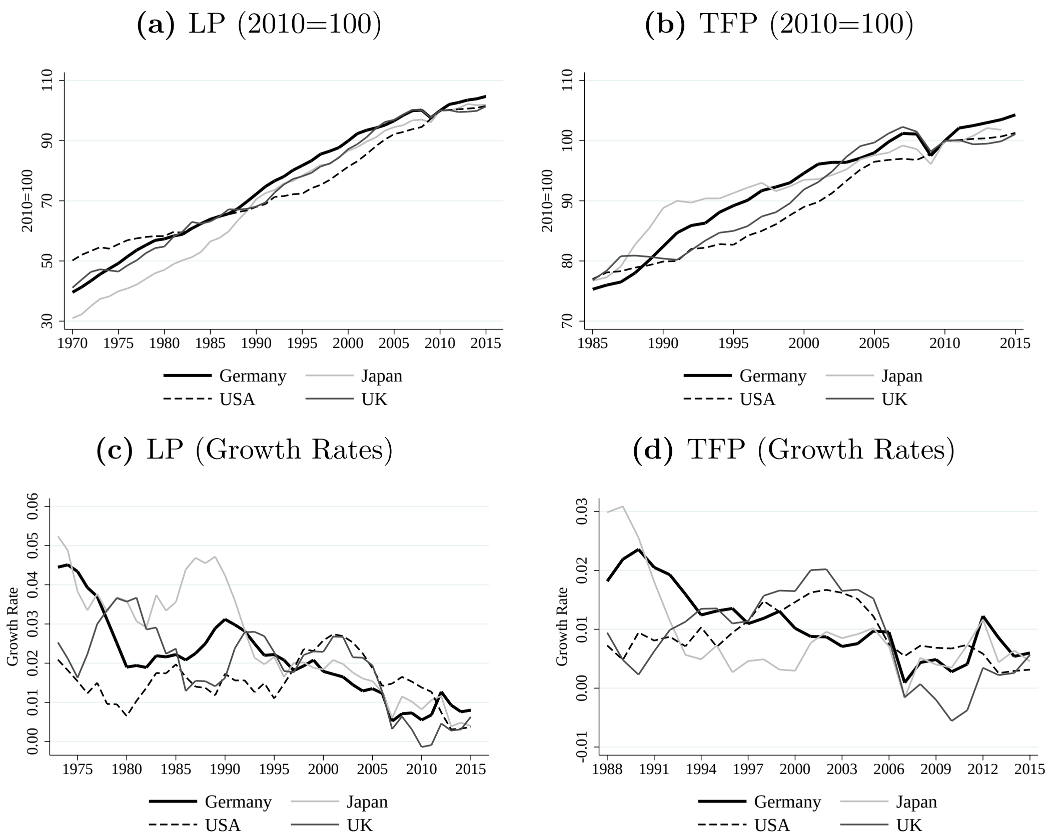
	Labour Productivity	Total Factor Productivity
1970-1980	3.78%	n.a.
1980-1990*	2.20%	1.82%
1990-2000	2.34%	1.53%
2000-2007	1.65%	1.07%
2010-2015	1.19%	1.15%
2012-2015	0.76%	0.54%

Source: OECD, own calculations. *For TFP only data after 1985 available.

[1] SMEs account for around 99 percent of all corporations in Germany and around 50 percent of gross value added (data provided by Destatis). They are hence important for the aggregate productivity development in Germany.

[2] The global productivity slowdown has spurred a lively debate on the underlying causes with explanations raging from structural causes such as ageing societies (Summers, 2013), to diminishing returns of innovation (Gordon, 2014), to errors in the measurement of productivity (Syverson, 2016).

Figure 4.1: Labour Productivity and Total Factor Productivity



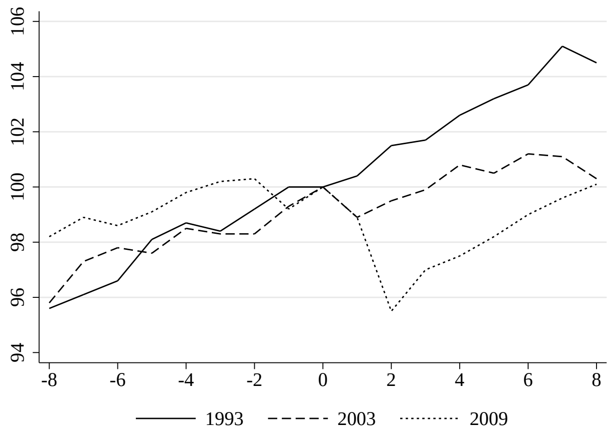
Source: OECD. Labour productivity (LP): GDP per hour worked, constant prices. Growth rates are the five year rolling average, including two preceding and two subsequent years.

Although a decline in productivity growth rates has been occurring for several decades, the period after 2007 is exceptional. The financial crisis and the subsequent recession during 2009 interrupted a trend of *positive* – though shrinking – productivity growth rates. Between 2008 and 2009, output per hour worked in Germany dropped by almost 2.6 percent. The TFP dropped by 3.6 percent. The substantial decline contrasted with the productivity dynamics of past recessions.[3] Figure 4.2 illustrates on a quarterly basis the development of labour productivity in Germany before, during and after the recessions in 1993, 2003 and 2009. During the 1993 recession, although labour productivity growth slowed for several quarters, output per hour did not decline and growth rates soon recovered to pre-crisis levels. During the 2003 recession, labour productivity contracted in one quarter, but recovered to pre-crisis

[3] Several papers have studied the dramatic productivity decline during the financial crisis. For the US Redmond and Van Zandweghe (2016) find that distressed credit markets significantly impeded TFP growth during the crisis years. They argue that an impaired access to credit curtailed research and development activities of the corporate sector thus impeding innovations. Franklin et al. (2015) empirically show for the UK that the reduction in credit supply following the financial crisis reduced investment, labour productivity and wages.

levels within three quarters. During the 2009 recession, labour productivity sharply declined in two consecutive quarters. It took another six quarters to recover to the levels of 2008. The post-crisis recovery has also been rather sluggish and growth rates as of 2012 have been particularly weak. Labour productivity growth dropped to an annual average of merely 0.76 percent, and TFP growth fell to 0.54 percent (Table 4.1).

Figure 4.2: Labour Productivity Germany - Previous Recessions



Source: Destatis, own calculations. Quarterly labour productivity index (GDP per hour worked). Base (t=0): 1992Q4 (Recession 1993), 2002Q4 (Recession 2003), 2008Q3 (Recession 2009).

A decline in productivity growth rates has long-term economic consequences. Figure 4.3 illustrates the trajectories of counterfactual growth paths of labour productivity and TFP – that assume productivity growth rates had remained at the pre-crisis level – compared with the actual productivity trends. If labour productivity had grown after the year 2000 at a constant annual rate of 1.65 percent – that is, if no financial crisis had interrupted the growth path – the labour productivity level would have been around 9 percent higher in 2015 than it actually was. The TFP would have been around 6 percent higher. If labour productivity growth had returned to its pre-crisis level after 2009, output per hour would have been around 3 percent higher than the actual 2015 level. Owing to the rather strong recovery of TFP growth in 2010/2011, the actual and counter-factual TFP levels are quite similar. However, if TFP growth remains as low as it has been since 2012, future TFP levels might fall below the projections based on pre-crisis growth rates.

Our analysis of German productivity data shows that productivity growth has not deteriorated solely in the wake of the financial crisis. However, it seems the crisis amplified pre-existing trends (Haldane, 2017). In the debate regarding the underlying

Figure 4.3: Productivity Growth Trends in Germany

(a) Labour Productivity **(b)** Total Factor Productivity

Source: OECD, own calculations. Actual: Index 2010=100. Trend 1: productivity trend based on 2000-2007 average growth rate, starting in year 2000. Trend 2: productivity trend based on 2000-2007 average growth rate, starting in year 2010.

causes of the post-crisis 'productivity puzzle', several studies have highlighted the role of economic and monetary policy interventions, and the consequences of those interventions for the restructuring and resource reallocation process in the corporate sector. (e.g. Arrowsmith et al., 2013; Broadbent et al., 2014; McGowan et al., 2017).

4.3 Impeded Capital Reallocation in a Low-Interest Rate Environment

The important role that corporate sector restructuring and resource reallocation play in aggregate productivity growth is well-established in the literature. Schumpeter (1942) coined the term 'creative destruction' to refer to the incessant process of replacing old, outdated products and production technologies with new ones through innovation. As previously bounded resources are set free by the destruction process, they can be shifted from sectors or production units that are contracting to those that are expanding. Hence an integral part of creative destruction is the reallocation of factors of production – that is, capital and labour – across production units. (Foster et al., 2001).

Factors of production move to where their marginal rates of return are highest, eventually equalizing these returns (Barnett et al., 2014). Hence, more productive firms offering higher rates of return attract capital and labour from less productive firms. The latter are forced to increase their productivity and efficiency or to leave the market, thereby freeing up resources. Hence creative destruction allows for a more efficient allocation of resources across the economy, leading to higher productivity growth at the aggregate level (Caballero and Hammour, 2000).

Central to the efficient allocation of capital across the economy are financial institutions (Wurgler, 2000). They provide a screening mechanism for the allocation of credit, by assessing which firms or projects are likely to yield the highest returns and transferring funds to those firms (Stiglitz and Weiss, 1988). Furthermore, they ensure that funds are used in the agreed manner, thereby playing a monitoring role (Stiglitz, 1989). Profit-maximizing financial institutions are expected to withdraw funds from poorly performing firms, which forces firms to improve their productivity and efficiency or to close down.

Empirical evidence suggests that the allocation of capital has become less efficient in the post-crisis period.[4] We argue that the ECB's ultra-loose monetary policy in the post-crisis period might have contributed to this development, as it has severely impaired the allocative function of financial institutions. The policy has undermined market discipline on the liability side of banks' balance sheets and has encouraged moral hazard on the asset side (Calderon and Schaeck, 2016). There are several channels through which a prolonged low-interest rate policy can disturb the efficient allocation of capital.

Firstly, banking sector restructuring is impeded. The financial crisis caused severe disruptions in the interbank market, tempting central banks to step in and act as lender of last resort (Garcia-de-Andoain et al., 2016). The supply of cheap and quasi-unlimited central bank liquidity has become the new normal as the EBC and other central banks have committed themselves to persistent monetary policy easing. Although the provision of low-cost liquidity is considered to have had a stabilizing effect, it impairs the Schumpeterian process of creative destruction by preventing or delaying a structural adjustment in the banking sector (Hoffmann and Schnabl, 2016). As under-capitalized and unviable banks – so called zombie banks – do not exit the market, they prey on the market share of healthy institutions.

Zombie banks are less likely than healthy banks to enforce discipline for distressed borrowers, but instead continue to roll over bad loans. In so doing they tie up resources with potentially less productive firms (Homar and van Wijnbergen, 2015). Peek and Rosengren (2005) show that in the 1990s, Japanese banks had an incentive

[4] For the UK, Broadbent et al. (2014) identify an increased dispersion of output prices across sectors arguing that this is a signal of impeded capital mobility because rates of return across sectors are not equalized. Also for the UK, Broadbent (2012, 2013) note that although sectoral rates of return on capital have significantly changed after the crisis, a subsequent movement of capital stock across sectors has not occurred. For the case of southern European countries Gopinath et al. (2015) find that the dispersion of the return to capital across firms significantly increased between 1999 and 2007 and further accelerated between 2008 and 2012.

to continue allocating credit to the weakest borrowers to avoid the realization of losses. Empirical studies on Japan have shown that the practice of forbearance lending has severely hampered resource reallocation from less-productive to more-productive firms, preventing the latter from gaining market shares (Ahearne and Shinada, 2005; Fukao and Kwon, 2006; Caballero et al., 2008). The problem of zombie banks and forbearance lending has also emerged in Europe. Albertazzi and Marchetti (2010) find evidence from small banks in Italy that forbearance lending took place in the period 2008/2009. Arrowsmith et al. (2013) show that around 6 percent of UK SME borrowers received some form of forbearance lending in March 2013.

Secondly, banks' lending behaviour is distorted. Although central banks' conventional and unconventional monetary policy measures have helped to keep banks alive, a prolonged period of ultra-low interest rates undermines commercial banks' traditional business model. The flattening of the yield curve depresses lending-deposit spreads which reduces banks' interest margins earned on traditional intermediation activities (for the case of Japan see Gerstenberger and Schnabl, 2017). This dynamic severely reduces banks' income and profitability (Borio et al., 2017; Busch and Memmel, 2015), which forces them to adjust their asset mix.

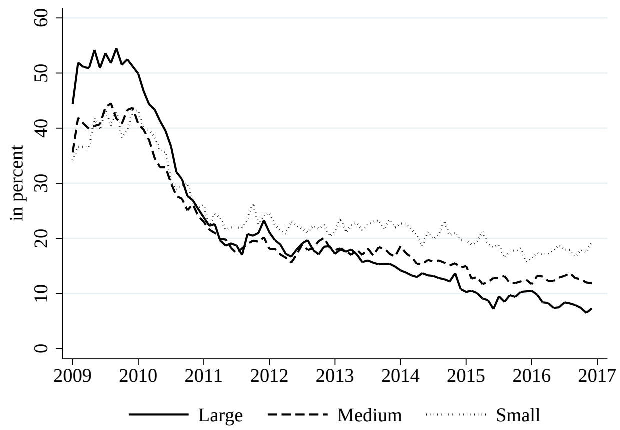
On the one hand, low interest rates can motivate financial intermediaries to lower their lending standards and ease credit access among riskier borrowers, due to an increased appetite and excessive tolerance of risk (Rajan, 2005; Dell'Ariccia and Marquez, 2006; Dell' Ariccia et al., 2010). Empirical evidence from the pre-crisis period clearly supports this notion.[5] On the other hand, low profits and profitability can impair banks' incentives and ability to supply loans to the corporate sector (Borio and Gambacorta, 2017). As a result, banks embark on a 'flight to quality'. Brunnermeier and Koby (2017) argue that low interest rates in combination with tighter financial regulations – as observed in the post-crisis period – reverse the intended expansionary credit-supply effect of an expansionary monetary policy. As interest margins shrink and banks' profits decline, regulatory equity constraints are tightened and banks are forced to reduce credit. Instead they scale up assets that

[5] Jiménez et al. (2014) find evidence for the Spanish banking sector that low short-term interest rates induced banks to lend more to risky borrowers. Maddaloni and Peydro (2011) find robust evidence that low short-term interest rates contributed to a softening of euro area and U.S. bank lending standards. Altunbas et al. (2010) find that the impact of low interest rates on banks' risk perception works inter alia through an increased search for yield. Low interest rates are argued to reduce banks' incentives to screen borrowers, thereby relaxing credit standards. For the German banking sector in the period 2005-2014 Memmel et al. (2016) show that below a certain profitability threshold banks search for yield by increasing their interest rate risk exposure.

are safe but lower in yield, such as government bonds; this further compresses the profit. Banks end up reducing their lending to comparatively high-risk borrowers such as SMEs or start-ups, and increase their lending to the public sector (Hoffmann and Schnabl, 2016).[6]

This trend has become particularly apparent in Japan (Schnabl, 2015). However, for Germany as well, an increasingly asymmetric access to credit is already being observed. While lending to large corporations has improved steadily since 2010, lending to small enterprises has shown a less pronounced recovery in recent years (Figure 4.4). Schwartz (2016) finds that micro-firms, in particular, had problems obtaining credit to realize their investment plans.

Figure 4.4: Access to Credit by Firm Size - German Manufacturing Sector



Source: Ifo Credit Constraint Indicator. Share of manufacturing sector firms reporting restrictive lending by the banks.

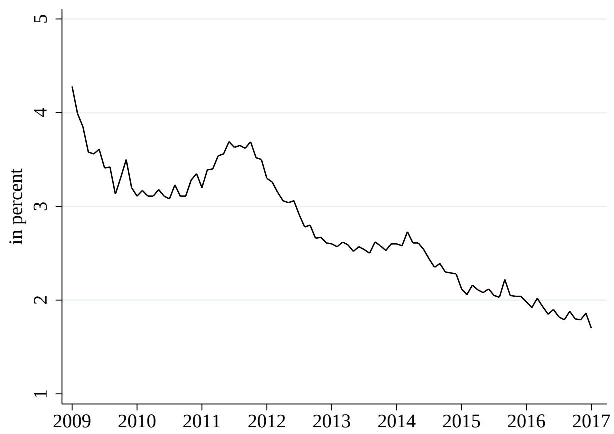
Thirdly, corporate sector restructuring is impeded due to low borrowing costs. The reduction of short- and long-term interest rates as a result of central banks' monetary policy interventions has substantially reduced firms' borrowing costs. The composite cost of borrowing indicator among German non-financial corporations (NFCs) – a weighted average of short- and long-term lending rates – dropped from a high of 6 percent in September 2008 to 1.7 percent in January 2017, as shown in Figure 4.5.

For any firm, as the cost of its external funding drops, interest expenses also decline and the firm's financial position strengthens (Gerstenberger, 2017). In that sense, low interest rates work as a kind of subsidy to the corporate sector. On the one hand, this is the intended effect of an expansionary monetary policy – in the hope of

[6] The purchase of government bonds receives preferential treatment by the Basel capital adequacy rules.

ultimately increasing investment spending and aggregate demand (Mishkin, 1996). On the other hand, the dynamic helps to lower the rate of business failure, thus slowing down the restructuring process in the corporate sector. As a result the share of less productive firms, whose economic viability becomes dependent on cheap credit, rises, and factors of production are tied up.

Figure 4.5: Borrowing Costs of German NFCs



Source: ECB. Cost of Borrowing Indicator defined as the average interest rate monetary financial institutions charged on new loans to the corporate sector.

Calligaris et al. (2016) observe that since 2008, firms operating at low productivity in the Italian non-manufacturing sector have had a higher chance of survival than before the crisis. For the UK, Barnett et al. (2014) find that the occurrence of firm liquidations has been rather low since the financial crisis, whereas the share of loss-making firms has increased. Chiu et al. (2014) estimate that labour productivity in the UK would have been 5 percent higher in 2011, had the death rate of firms after the financial crisis been as high as in the 1990s. A similar development can be observed in Germany. The annual number of business failures is at an all-time low, as shown in Figure 4.6, while the share of German SMEs with poor creditworthiness has increased (Gerstenberger and Zimmermann, 2016).

The decline in interest expenses due to a prolonged period of artificially low interest rates might not only affect the allocation of capital by slowing the reallocation process; it can also lead to inefficient use of resources by the firms themselves. Hoffmann and Schnabl (2016) argue that the expectation of a continuous supply of cheap credit reduces firms' motivation to cut costs and pursue innovation, because the pressure to generate profit through greater efficiency declines. In addition, Forbes (2015) questions whether low interest rates reduce firms' incentives to carefully assess and evaluate their investment projects; if so, a less efficient use of capital is likely.

Figure 4.6: Number of Corporate Insolvencies in Germany (1999-2016)

Source: Creditreform.

4.4 Empirical Evidence from German SMEs

Although several studies have analysed the weak productivity trends in the German corporate sector (e.g. Erber and Hagemann, 2012; Schneider, 2013; Eichert and Frisse, 2016), no study known to us has empirically tested the connection between the low-interest rate environment and the efficiency of resource reallocation. We therefore analyse whether the post-crisis productivity slowdown of the German corporate sector has been influenced by an impeded capital reallocation process. To evaluate the efficiency of the capital allocation process we focus on the link between a firm's productivity and its success in applying for bank loans.

For our analysis we use the *KfW Mittelstandspanel*, a representative annual survey covering German micro, small and medium-sized enterprises with an annual turnover of less than EUR 500 million. The dataset comprises qualitative and quantitative data from 60,653 firms covering a period of 14 years (2002–2015). In addition to firm characteristics, the dataset includes information on bank loan applications. To control for outliers, we discard firm-year observations that belong to the 1st or 99th percentile of the variables of interest. Taking into account missing observations, the final sample contains 16,105 observations of 8,481 SMEs for the period 2005–2015.[7]

[7] Our estimation sample covers less years than the original sample due to some variables being not available for all survey years.

The sample is unbalanced owing to missing data and differing participation behaviour among the firms.[8]

In the survey, firms are asked whether they applied for bank loans to finance their investment projects, and if so, whether the applications were (a) completely successful, (b) partly successful or (c) not successful at all. Based on these data we construct three indicators for a firm's loan application success (LAS):

- $AllSucc$ takes the value of 1 if all loan applications were successful, and 0 otherwise;
- $PartSucc$ takes the value of 1 if only some – but not all – loan applications were successful, and 0 otherwise;
- $NoSucc$ takes the value of 1 if no loan application was successful, and 0 otherwise.

In a market economy, firms that are productive should have a relatively good chance of successfully applying for a bank loan. To test this relationship, we estimate the following model:

$$LAS_{i,t} = \alpha + \beta LP_{i,t-1} + \gamma X_{i,t} + \lambda_{j,t} + \epsilon_{i,t} \tag{4.1}$$

where $LAS_{i,t}$ is one of the binary indicators of loan application success of firm i in year t as described above. Hence, equation (4.1) is estimated for three different dependent variables: $AllSucc$, $PartSucc$ and $NoSucc$. The term $LP_{i,t-1}$ refers to firm i's labour productivity, lagged by one period to mitigate problems of simultaneity. In line with previous studies, we define labour productivity as the natural logarithm of real turnover divided by the number of full time employees (FTE) (e.g. Baumann and Kritikos, 2016).[9] Based on our theoretical considerations, presented in the previous section, we expect that more productive firms would be more likely to successfully complete loan applications. Hence, we expect β to be positive for $AllSucc$ and negative for $PartSucc$ and $NoSucc$.

The term X is a vector comprising firm-specific control variables that are expected to affect a firm's loan application success. We include the firm's creditworthiness CW

[8] For more information on the sample structure see Appendix C.1.

[9] A more accurate measure of labour productivity is gross value added (GVA) over FTE. However, firm specific information of GVA are not available in our dataset. Comparing aggregate data on turnover/FTE and GVA/FTE provided by the German statistical office reveals that for the case of SMEs both measures are fairly similar.

approximated by the *Creditreform Creditworthiness Indicator*[10] as measured at the beginning of year t. This score is an indicator for the firm's default probability; it is measured on a scale of 100 to 600, with lower values indicating higher creditworthiness. We expect creditworthiness to have a positive effect on a firm's success in applying for loans.

Furthermore, we control for firm size, measured as the natural logarithm of total assets TA, lagged by one year to mitigate the possibility of simultaneity. We also control for the age of the firm, AGE, defined as the natural logarithm of the number of years the firm has been operating. We include the control variable $LOAN$ which captures the size of the loans applied for (in million euro). We expect larger loans to be more difficult for SMEs to obtain. Summary statistics and variable definitions are provided in Table C.4 and Table C.3 in Appendix C.1. Furthermore, we control for industry-year fixed effects $\lambda_{j,t}$. The term $\epsilon_{i,t}$ is the idiosyncratic error term, assumed to be identically and independently distributed.

In a second step, we test whether the effect of productivity on loan application success was different before, during and after the financial crisis. We interact $LP_{i,t-1}$ with dummy variables indicating the periods of crisis (2008–2009) or post-crisis (2010–2015):

$$
\begin{aligned}
LAS_{i,t} = \alpha + \beta_1 LP_{i,t-1} + \beta_2 LP_{i,t-1} {}^* Crisis_t + \beta_3 LP_{i,t-1} {}^* PostCr_t + \\
\gamma X_{i,t} + \lambda_{j,t} + \epsilon_{i,t}
\end{aligned}
\tag{4.2}
$$

In this model the coefficient β_1 captures the effect of labour productivity on loan application success in the pre-crisis period. The coefficients β_2 and β_3 capture the difference between the pre-crisis productivity-effect and the effect in the crisis and post-crisis period, respectively. If the resource allocation process has been less efficient since the start of the financial crisis, and more capital has been allocated to less productive firms, β_2 and β_3 should be negative in the model with $ALLSucc$ being the dependent variable. Conversely, under the same conditions, β_2 and β_3 should be positive in the models, with $PartSucc$ and $NoSucc$ being the dependent variables.

Although the binary nature of the dependent variables requires the use of a non-linear model, we estimate models (4.1) and (4.2) using a fixed-effects linear probability

[10] The Creditreform Creditworthiness Indicator is calculated based on information of the firm's liquidity, profit and asset position. It also takes into account structural risks such as firms size and legal form as well as sectoral risks (Creditreform, 2015).

model to avoid selection problems.[11] Jiménez et al. (2012) point out that the main advantage of using a linear probability model is the intuitive interpretation of the interaction terms' coefficients – which are the main focus of our empirical analysis. Furthermore, standard errors of interaction terms do not require correction, as is the case for non-linear models (Ai and Norton, 2003; Norton et al., 2004). We additionally estimate logit models as a robustness check (Appendix C.3).

Estimation Results

In columns (1), (3) and (5) of Table 4.2 we report the estimation results of the baseline model (4.1) for each of the three dependent variables. In all estimations the coefficient of labour productivity has the expected sign and is statistically significant, except for the model with $PartSucc$ as dependent variable. The positive coefficient in the model with *AllSucc* (column 1) indicates that lower labour productivity decreases the probability of all bank loan applications being accepted. The corollary is the negative coefficients obtained in the other models. These indicate that lower labour productivity increases the probability of the firm having its loan applications only partly accepted (column 3) or not accepted at all (column 5). This finding implies – as discussed above – that a firm's labour productivity has a credit-rationing and hence allocative effect.[12]

Furthermore, the creditworthiness indicator is statistically significant in columns (1) and (5). A higher value (i.e. lower creditworthiness) reduces the probability of all loan applications being accepted, and increases the probability of having no successful application. This finding is in line with our theoretical assumptions. The results for the remaining control variables are inconclusive, with most coefficients not being statistically significant.

In columns (2), (4) and (6) of Table 4.2 we report the estimation results for model (4.2), which includes interaction terms of labour productivity, with two dummies for the two stages of the post-2007 period: $Crisis$ and $PostCr$. In this model the coefficient of labour productivity represents the pre-crisis relationship between productivity

[11] Using a fixed-effects logit model would restrict our sample to only those firms who at least one time completed all loan applications successfully (*AllSucc* =1) and one time not (analogously for $PartSucc$ and $NoSucc$).

[12] Our results indicate that a 30 percent reduction in firm's labour productivity (equivalent to the standard deviation of labour productivity growth in our sample) is associated with a 1.3 percentage point decline (ln(0.7)*0.0370= -0.0132) in the probability of having all loan applications accepted and a 0.64 p.p. (0.59 p.p.) increase in the probability of having only some (no) loan applications accepted.

and loan application success. The interaction terms capture the change in this relationship during the crisis and the post-crisis period. The labour productivity coefficients are larger in value than in the baseline estimation and are statistically significant for all three dependent variables. Hence, the isolated pre-crisis impact of labour productivity on the loan application success is much larger than the effect measured for the total sample.

Table 4.2: Results - Baseline Model and Crisis Model

	(1) AllSucc	(2) AllSucc	(3) PartSucc	(4) PartSucc	(5) NoSucc	(6) NoSucc
$LP_{i,t-1}$	0.0370***	0.0867***	-0.0180	-0.0365*	-0.0167*	-0.0491***
	[0.0139]	[0.0197]	[0.0131]	[0.0195]	[0.0096]	[0.0131]
$LP_{i,t-1}$*$Crisis_t$		-0.0395**		0.0099		0.0309**
		[0.0185]		[0.0181]		[0.0124]
$LP_{i,t-1}$*$PostCr_t$		-0.0754***		0.0303*		0.0467***
		[0.0193]		[0.0178]		[0.0117]
$CW_{i,t}$	-0.0006**	-0.0005**	0.0001	0.0001	0.0005**	0.0004**
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0002]
$TA_{i,t-1}$	-0.0040	0.0005	-0.0069	-0.0086	0.0151	0.0122
	[0.0149]	[0.0149]	[0.0135]	[0.0136]	[0.0100]	[0.0100]
$AGE_{i,t}$	-0.0031	-0.0332	0.0164	0.0293	-0.0081	0.0097
	[0.0610]	[0.0612]	[0.0540]	[0.0549]	[0.0420]	[0.0421]
$LOAN_{i,t}$	-0.0106	-0.0097	0.0239***	0.0235***	-0.0115***	-0.0120***
	[0.0083]	[0.0084]	[0.0078]	[0.0078]	[0.0044]	[0.0044]
Constant	0.6528*	0.1097	0.2031	0.4042	0.0515	0.4070
	[0.3577]	[0.3886]	[0.3311]	[0.3658]	[0.2288]	[0.2479]
Observations	16,105	16,105	16,105	16,105	16,105	16,105

Notes: Estimated using a fixed-effects linear probability model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of industry-year fixed effects. Standard errors in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Furthermore, except for the model in which $PartSucc$ is the dependent variable, the coefficients for the $Crisis$ and $PostCr$ interaction terms are statistically significant. This finding implies that the relationship between labour productivity and loan application success changed during the crisis and the post-crisis periods, compared with the years before 2008. For *AllSucc*, the coefficients of both interaction terms are negative; for $NoSucc$ they are positive. This implies that the credit-rationing effect of labour productivity has declined since 2008.

In all three estimations, the coefficients for the $PostCr$ interaction terms are larger in value than the $Crisis$ interaction terms. This indicates that the allocative effect of labour productivity has been even lower during the post-crisis period than during the financial crisis itself. Compared with the pre-crisis years, the effect of labour productivity on loan application success dropped by around 82 to 95 percent after 2009.[13] This large decline has reduced the credit-rationing effect of labour productivity almost to zero.

Table 4.3: Results - Sample Split by Sector

AllSucc	(1) MN	(2) CONST	(3) TRD	(4) SV	(5) OTH
Pre-Crisis	0.1250***	0.1185**	0.0446	0.0631	0.0194
	[0.0341]	[0.0487]	[0.0343]	[0.0387]	[0.1813]
Crisis	0.04431	0.0513	0.0298	0.0282	0.0284
	[0.0339]	[0.0522]	[0.0265]	[0.0284]	[0.1059]
Post-Crisis	0.0613**	-0.0013	-0.0170	-0.0318	-0.0483
	[0.0308]	[0.0273]	[0.0279]	[0.0289]	[0.0804]
Observations	5,194	2,615	5,364	3,937	467

Notes: *AllSucc* is the dependent variable. Pre-Crisis: $LP_{i,t-1}$ coefficient estimated using model (4.2). Crisis: sum of $LP_{i,t-1}$ and $LP_{i,t-1}$*$Crisis_t$. Post-Crisis: sum of $LP_{i,t-1}$ and $LP_{i,t-1}$*$PostCr_t$. MN-manufacturing, CONST-construction, TRD-Trade, SV-Services, OTH-other industries. All models estimated using a fixed-effects linear probability model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of firm-specific control variables and industry-year fixed effects. Standard errors in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

The results of both our baseline and extended model are robust to alternative estimation methods. Using a fixed-effects logit model as robustness check, our estimation results do not change in terms of coefficient sign and significance (see Table C.8 and C.9 in Appendix C.3). To evaluate whether the results are driven by a subgroup of firms, we split the sample and re-estimate model (4.2) for different sectors: manufacturing, construction, trade, services and other industries. For brevity we only discuss the results for *AllSucc*.[14] The results are summarized in Table 4.3. The second row shows the pre-crisis labour productivity impact, namely the $LP_{i,t-1}$ coefficient from model (4.2). The third row shows the labour productivity impact during the crisis period, calculated by adding up the $LP_{i,t-1}$ and $LP_{i,t-1}$*$Crisis_t$ coefficients. The fourth row shows the post-crisis impact of labour productivity.[15]

Our estimation results suggest that the pre- and post-crisis effect of labour productivity on firms' loan application success differs by sector. For the manufacturing and construction sectors, we find a large, statistically significant credit-rationing effect

[13] For the case of *AllSucc*: 87 percent (0.0754/0.0867=0.8697); for *PartSucc*: 82 percent; for *NoSucc*: 95 percent.
[14] Complete estimation results for all depended variables are provided in Appendix C.2.
[15] Standard errors are computed using the delta method.

of labour productivity in the years before the financial crisis. However, no similar significant effect is found for the trade sector, the service sector and other industries.

The results also confirm that the credit-rationing effect of labour productivity has changed since the crisis. For the manufacturing sector, the effect size has dropped by around 50 percent. In the construction sector the difference is even stronger. For this sector we find that since 2010, the credit-rationing effect of labour productivity has been reduced to almost zero. The strong post-crisis change for the construction sector might be a symptom of the German construction boom that occurred after the crisis.[16] For the remaining sectors, the effect of labour productivity on loan application success remains statistically not significant.

To sum up, the results indicate that ceteris paribus, a firm with a constant low productivity level has had easier access to credit during the crisis and post-crisis periods than it did pre-crisis. This particularly applies to SMEs in the construction sector but also in the manufacturing sector. These findings might imply that the capital allocation process has become less efficient since 2008, as more loans are directed to less productive firms. In addition, due to the provision of funds these firms might have had a better chance of survival post-crisis than pre-crisis. As the share of low-productive firms increases, the aggregate productivity declines. Hence, our findings indicate that the post-crisis productivity slowdown in the German corporate sector might have been caused partly by misdirection of credit to less productive firms.

4.5 Conclusion

Productivity growth in Germany has been rather weak in the post-crisis period. We argue that the ECB's ultra-loose monetary policy which was adopted to curtail the negative impacts of the financial crisis and the following sovereign debt crisis has contributed to the productivity slowdown because it distorted the efficient allocation of capital. Using firm-level data from German SMEs, we provide empirical evidence that during the post-crisis period low-productive firms have had easier access to credit. This could have increased their odds of survival and lowered the incentive for them to increase their efficiency and productivity. The impaired reallocation and restructuring process is likely to have contributed to the weak growth of productivity

[16] This development increases the danger of misdirecting credit to the less-productive construction and real estate sector.

in Germany.

Our findings highlight the adverse economic consequences of a prolonged period of ultra-low interest rates and unconventional monetary policy measures. As productivity growth is suppressed, potential output is likely to remain low as well. This causal direction – low interest rates cause low productivity growth, which in turn cause low GDP growth – stands in contrast to the *secular stagnation* hypothesis (e.g. Summers, 2013). Our findings lend support to the argument that low interest rates cause low growth (e.g van den End and Hoeberichts, 2014; Ciżkowicz and Rzońca, 2014; Hoffmann and Schnabl, 2016).

Appendix C

C.1 Sample Structure and Variable Definition

Table C.1: Number of Observations by Year

Year	Observations
2005	1,155
2006	1,505
2007	1,419
2008	2,188
2009	1,824
2010	1,205
2011	1,472
2012	1,508
2013	1,444
2014	1,303
2015	1,082
Total	16,105

Table C.2: Number of Firms by Sector

Sector	No. of Firms
Manufacturing	2,672
Construction	1,350
Retail Trade	1,448
Wholesale Trade	793
Services	1,994
Others	244

Table C.3: Variable Definition

Dependent Variables	
AllSucc	1: All bank loan applications successful 0: Otherwise
PartSucc	1: Some (but not all) bank loan applications successful 0: Otherwise
NoSucc	1: No bank loan application successful 0: Otherwise
Independent Variables	
LP	Natural lof of real turnover/full time employees
CW	Creditreform Creditworthiness Indicator
TA	Natural log of real total assets
AGE	Natural log of one plus age of firm
LOAN	Amount of loans applied for (in million EUR)

Table C.4: Descriptive Statistics

	Mean	SD	Min	Max
AllSucc	0.72	0.45	0	1
PartSucc	0.16	0.37	0	1
NoSucc	0.11	0.31	0	1
LP	11.82	0.75	8.72	14.25
CW	232.16	46.94	100	600
TA	14.74	1.48	0.01	21.25
AGE	3.36	0.86	1.10	6.49
LOAN	0.47	0.71	0.00	4.50

Notes: LP, CW, TA and AGE in natural logs. Loan in million EUR.

C.2 Results by Sector

Table C.5: Results AllSucc - Sample Split by Sector

AllSucc	(1) MN	(2) CONST	(3) TRD	(4) SV	(5) OTH
$LP_{i,t-1}$	0.1250***	0.1185**	0.0446	0.0631	0.0194
	[0.0341]	[0.0487]	[0.0343]	[0.0387]	[0.1813]
$LP_{i,t-1}{*}Crisis_t$	-0.0807***	-0.0672	-0.0148	-0.0348	0.0090
	[0.0289]	[0.0533]	[0.0278]	[0.0353]	[0.1715]
$LP_{i,t-1}{*}PostCr_t$	-0.0637**	-0.1198**	-0.0616**	-0.0949**	-0.0676
	[0.0323]	[0.0510]	[0.0313]	[0.0382]	[0.1601]
$CW_{i,t}$	-0.0007*	-0.0002	-0.0007	-0.0003	-0.0022
	[0.0004]	[0.0005]	[0.0005]	[0.0005]	[0.0017]
$TA_{i,t-1}$	-0.0202	-0.0011	0.0239	0.0492	0.1528**
	[0.0290]	[0.0224]	[0.0306]	[0.0343]	[0.0749]
$AGE_{i,t}$	-0.0650	0.0317	-0.0494	-0.0182	-0.3741
	[0.1032]	[0.1322]	[0.1240]	[0.1433]	[0.5090]
$LOAN_{i,t}$	0.0077	-0.0208	-0.0394***	-0.0506***	-0.0138
	[0.0123]	[0.0326]	[0.0133]	[0.0158]	[0.0559]
Constant	-0.1664	-0.7777	0.0701	-0.6512	-0.3431
	[0.6096]	[0.7272]	[0.7060]	[0.7861]	[2.6032]
Observations	5,194	2,615	5,364	3,937	467

Notes: *ALLSucc* is the dependent variable. MN-manufacturing, CONST-construction, TRD-Trade, SV-Services, OTH-other industries. All models estimated using a fixed-effects linear probability model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of firm-specific control variables and industry-year fixed effects. Standard errors in parentheses, $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table C.6: Results PartSucc - Sample Split by Sector

$PartSucc$	(1) MN	(2) CONST	(3) TRD	(4) SV	(5) OTH
$LP_{i,t-1}$	-0.0323	-0.1037*	-0.0180	-0.0098	-0.1299
	[0.0337]	[0.0575]	[0.0310]	[0.0365]	[0.1742]
$LP_{i,t-1}$*$Crisis_t$	0.0153	0.0813	0.0071	0.0034	0.0157
	[0.0302]	[0.0605]	[0.0234]	[0.0312]	[0.1658]
$LP_{i,t-1}$*$PostCr_t$	0.0038	0.1044*	0.0366	0.0388	0.0740
	[0.0293]	[0.0538]	[0.0270]	[0.0343]	[0.1513]
$CW_{i,t}$	-0.0000	-0.0004	0.0006	0.0001	0.0028*
	[0.0003]	[0.0005]	[0.0005]	[0.0005]	[0.0016]
$TA_{i,t-1}$	-0.0090	0.0069	-0.0228	-0.0448	-0.0389
	[0.0266]	[0.0232]	[0.0275]	[0.0309]	[0.0647]
$AGE_{i,t}$	0.0431	0.0172	0.0279	0.0214	0.1556
	[0.0946]	[0.1367]	[0.0991]	[0.1123]	[0.4637]
$LOAN_{i,t}$	0.0116	0.0454	0.0444***	0.0475***	0.0373
	[0.0113]	[0.0340]	[0.0125]	[0.0153]	[0.0451]
Constant	0.5911	1.3527*	0.5513	0.8772	1.4350
	[0.5661]	[0.8144]	[0.5772]	[0.6466]	[2.4517]
Observations	5,194	2,615	5,364	3,937	467

Notes: $PartsSucc$ is the dependent variable. MN-manufacturing, CONST-construction, TRD-Trade, SV-Services, OTH-other industries. All models estimated using a fixed-effects linear probability model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of firm-specific control variables and industry-year fixed effects. Standard errors in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table C.7: Results NoSucc - Sample Split by Sector

$NoSucc$	(1) MN	(2) CONST	(3) TRD	(4) SV	(5) OTH
$LP_{i,t-1}$	-0.0827***	-0.0336	-0.0244	-0.0520**	0.0805
	[0.0222]	[0.0373]	[0.0220]	[0.0247]	[0.0645]
$LP_{i,t-1}$*$Crisis_t$	0.0580***	0.0070	0.0095	0.0269	-0.0276
	[0.0210]	[0.0405]	[0.0161]	[0.0219]	[0.0468]
$LP_{i,t-1}$*$PostCr_t$	0.0566***	0.0285	0.0256	0.0587***	-0.0145
	[0.0191]	[0.0382]	[0.0177]	[0.0216]	[0.0471]
$CW_{i,t}$	0.0005*	0.0007*	-0.0000	0.0002	-0.0009
	[0.0003]	[0.0004]	[0.0004]	[0.0004]	[0.0006]
$TA_{i,t-1}$	0.0234	0.0070	0.0046	0.0022	-0.1092**
	[0.0164]	[0.0154]	[0.0207]	[0.0238]	[0.0477]
$AGE_{i,t}$	0.0434	-0.0538	0.0132	-0.0223	0.2037
	[0.0611]	[0.1002]	[0.0892]	[0.1063]	[0.1729]
$LOAN_{i,t}$	-0.0191***	-0.0177	-0.0036	0.0016	-0.0170
	[0.0070]	[0.0225]	[0.0059]	[0.0075]	[0.0239]
Constant	0.5025	0.4313	0.3129	0.7136	0.3003
	[0.3334]	[0.5300]	[0.5065]	[0.5723]	[0.7797]
Observations	5,194	2,615	5,364	3,937	467

Notes: $NoSucc$ is the dependent variable. MN-manufacturing, CONST-construction, TRD-Trade, SV-Services, OTH-other industries. All models estimated using a fixed-effects linear probability model. Standard errors are adjusted for heteroscedasticity and clustering at the firm level. Inclusion of firm-specific control variables and industry-year fixed effects. Standard errors in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

C.3 Robustness Checks

Table C.8: Robustness Check - Logit Model (1)

	(1) AllSucc	(2) PartSucc	(3) NoSucc
$LP_{i,t-1}$	0.3624***	-0.1475	-0.3368*
	[0.1364]	[0.1380]	[0.1876]
$CW_{i,t}$	-0.0046**	0.0008	0.0061***
	[0.0018]	[0.0019]	[0.0023]
$TA_{i,t-1}$	-0.0709	-0.0571	0.1972
	[0.1025]	[0.1131]	[0.1555]
$AGE_{i,t}$	-0.0884	0.3218	0.2962
	[0.4751]	[0.5202]	[0.6863]
$LOAN_{i,t}$	-0.0624	0.2110***	-0.3306***
	[0.0670]	[0.0734]	[0.1271]
Observations	4,439	3,885	1,858

Notes: Estimated using a fixed-effects logit model. Inclusion of industry-year fixed effects. Standard errors in parentheses, $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table C.9: Robustness Check - Logit Model (2)

	(1) AllSucc	(2) PartSucc	(3) NoSucc
$LP_{i,t-1}$	0.6789***	-0.2690	-0.8882***
	[0.1734]	[0.1684]	[0.2626]
$LP_{i,t-1}*Crisis_t$	-0.2798**	0.0754	0.7288***
	[0.1402]	[0.1454]	[0.2339]
$LP_{i,t-1}*PostCr$	-0.4971***	0.2272	0.6528***
	[0.1431]	[0.1489]	[0.2343]
$CW_{i,t}$	-0.0044**	0.0006	0.0060***
	[0.0018]	[0.0019]	[0.0023]
$TA_{i,t-1}$	-0.0338	-0.0749	0.1541
	[0.1029]	[0.1137]	[0.1560]
$AGE_{i,t}$	-0.3517	0.4344	0.5857
	[0.4840]	[0.5254]	[0.7090]
$LOAN_{i,t}$	-0.0476	0.2049***	-0.3770***
	[0.0672]	[0.0735]	[0.1308]
Observations	4,439	3,885	1,858

Notes: Estimated using a fixed-effects logit model. Inclusion of industry-year fixed effects. Standard errors in parentheses, $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Chapter 5

The Impact of the Bank of Japan's Crisis Management on the Japanese Banking Sector

Together with Gunther Schnabl

Abstract

This paper presents an analysis of the impact of the Bank of Japan's crisis management on the banking sector in the wake of the 1998 Japanese financial crisis. We describe how the low-cost liquidity provision as a means to stabilize banks has created a growing gap between deposits and loans in the financial system. Furthermore, we show that the low-interest rate policy has compressed interest margins as the traditional source of banks' income. Efficiency scores are compiled to estimate the effect of the Bank of Japan's crisis management on banks' technical efficiency. The estimation results provide evidence that the Japanese monetary policy has contributed to declining efficiency in the banking sector, despite – or perhaps because of – the increasing concentration within this sector.

5.1 Introduction

During the second half of the 1980s, the Bank of Japan introduced a low-interest rate policy to mitigate the appreciation pressure on the Japanese yen.[1] This policy contributed to the emergence of a 'bubble' in the Japanese stock and real estate markets, which ended in the early 1990s (Bayoumi and Collyns, 2000). During most of the 1990s, the destabilizing effect of the resulting balance-sheet recession (Koo, 2003) was contained by the Bank of Japan gradually cutting the interest rate to almost zero. This enabled Japanese banks to cover their losses, incurred from declining asset prices, by providing credit to Japanese enterprises operating in Southeast Asia (Hoffmann and Schnabl, 2008). The 1997/98 Asian crisis, however, finally triggered strong adjustment pressure on the Japanese banking sector (Schnabl, 2015). This development accompanied a consolidation process among Japanese banks and financial institutions (Hosono et al., 2009).

The continuation of the zero-interest rate policy after 1999, and the advent of unconventional monetary policy measures, have been widely understood as stabilizing measures for the Japanese banking sector (Posen, 2000; Koo, 2003). The ample low-cost liquidity provision of the Bank of Japan stabilized asset prices while also stabilizing the banks' balance sheets by reducing the number of potential bad loans. However, the liquidity provisions of the Bank of Japan arguably prevented Schumpeter's (1942) process of 'creative destruction' and thereby thwarted sustained recovery among Japanese banks (Sekine et al., 2003; Peek and Rosengren, 2005; Caballero et al., 2008). In this regard, the effect of the Bank of Japan's' crisis management – in the form of a zero interest rate policy and monetary expansion – on the Japanese banking sector is ambiguous from a theoretical point of view.

Previous empirical studies have shown that the Japanese banking sector exhibits major technical and scale inefficiencies, with considerable differences among the various bank types (Fukuyama, 1993; McKillop et al., 1996; Altunbas et al., 2000; Drake and Hall, 2003; Drake et al., 2009; Assaf et al., 2011). However, few studies have attempted to understand the impact of the Bank of Japan's crisis management on the efficiency of the banking sector. Therefore, we add to the existing literature by analysing the adjustment of Japanese banks to the low-interest rate policy and the unconventional monetary policy measures. Based on micro-data, we empirically

[1] The Bank of Japan cut short-term interest rates from roughly 8 percent in 1985 to 3.5 percent in 1987.

test the determinants of Japanese banks' technical efficiency while controlling for their adjustment to the Bank of Japan's monetary policy.

5.2 Japan's Low-Interest Rate Policy and the Banking Sector

The development of the Japanese banking sector since the 1998–99 Japanese financial crisis must be seen in the context of protracted stagnation in the domestic economy (Schnabl, 2015). During the Japanese bubble economy (1985–1990), domestic banks' credit to the private sector grew markedly, with credit slowly continuing to expand until 1998. With the Asian and Japanese financial crises, a credit crunch set in (Ishikawa and Tsutsui, 2005), which can be seen as driven by either supply or demand. The gradual erosion of the banks' traditional sources of income triggered a search for alternative revenues and a struggle to increase their efficiency through mergers and acquisitions (M&A).

5.2.1 Declining Income

The credit crunch, which lasted from 1998 until the advent of *Abenomics*[2] in January 2013, had two origins. On the one hand, declining asset prices forced Japanese banks to reduce their risk exposure by curtailing outstanding credit to risky enterprises (Koo, 2003). On the other hand, sluggish investment by the corporate sector and the need to deleverage lowered the demand by Japanese firms for loans, while simultaneously increasing their deposits at banks. In this context, the zero-interest rate policy and unconventional monetary policy measures can be understood as a form of subsidy for enterprises – in particular, large enterprises.[3] The resulting growth in cash reserves further reduced their demand for credit (Gerstenberger, 2017).

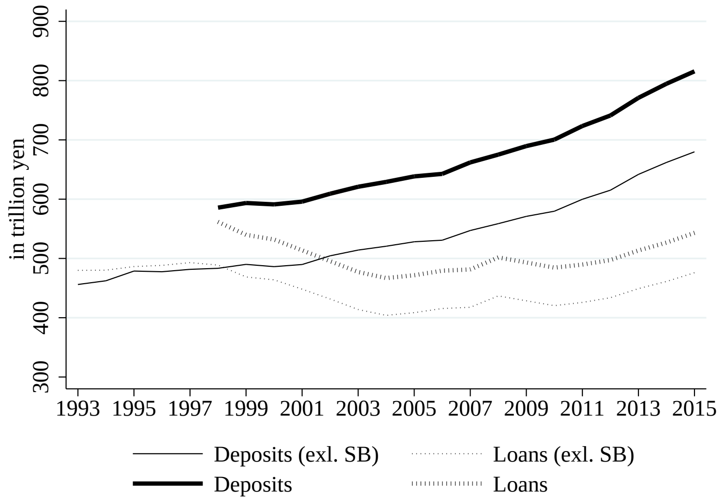
As a result, the total amount of loans reflected on the balance sheets of banks fell substantially. The increasing inflow of personal and corporate deposits, combined with declining volumes of credit, led to a widening gap between loans and deposits (Figure 5.1). The credit business started to recover only from 2012 but without

[2] *Abenomics* refers to Japanese Prime Minister Shinzo Abe's three-pillared policy package to revive the Japanese economy, comprising monetary easing, fiscal expansion and structural reforms.

[3] The low-interest rate policy reduced the financing costs of enterprises by continuously depressing interest rates. In addition, the resulting depreciation of the yen subsidized large export-oriented enterprises.

helping to reduce the gap. The loan–deposit ratio fell from almost 1 at the beginning of the 1990s to less than 0.7 in 2015.

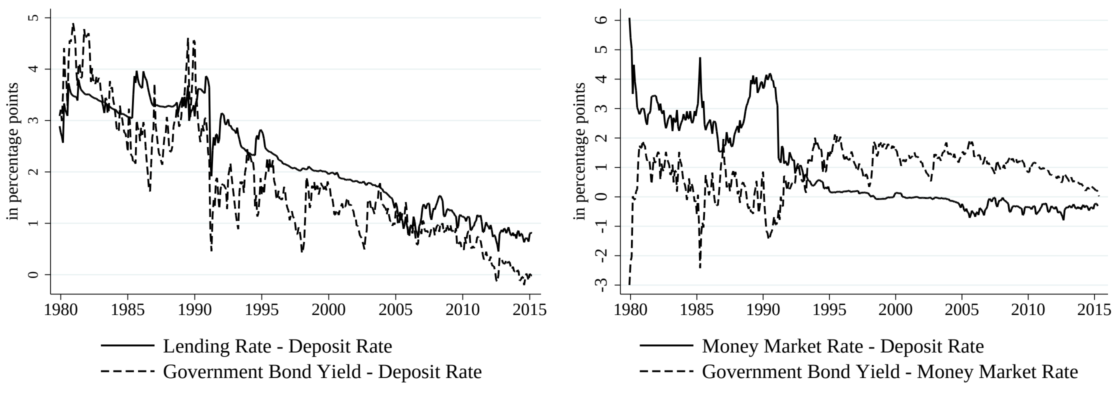
Figure 5.1: Deposits and Loans at Japanese Banks



Source: Bank of Japan. Data for shinkin banks (SB) were not available for the period before 1999.

Figure 5.2: Interest Rate Spreads in the Japanese Banking Sector

(a) Spreads 1 **(b)** Spreads 2



Source: IMF, own calculations. Government bond yields on the 10-year government bonds. Interest rates on new contracts.

The stagnation in the traditional credit business became paired with declining margins in the loans and investment business. The Bank of Japan's monetary policy gradually depressed the short-term money market rates, which finally dropped to zero in March 1999. The Bank of Japan continued to reduce interest rates at the long end of the yield curve through fast-growing bond purchases (Yoshino and Taghizadeh-Hesary, 2016).[4] As a result, the spread between average lending and deposit rates (on new contracts) declined from an average of 3.5 percentage points during the 1980s to currently less than 1 percentage point, as shown in Figure 5.2a.

Japanese banks partially substituted the decline in lending to the private sector by the purchase of government bonds (see Section 5.2.2). However, the margin between the government bond yield and the deposit rate also declined from 3.5 percentage points in the 1980s to close to (or below) zero during the Abenomics period (Figure 5.2a). The scope for generating profits by transforming short-term borrowing in the money market into long-term lending also shrank. The transformation margin can be defined as the spread between the government bond yield and the money market rate. This margin declined from a peak of close to 2 percentage points in 1996 to zero at present (Figure 5.2b). Moreover, the passive margin – the difference between the money market rate and the average deposit rate – dropped from around 3 percentage points in the 1980s to zero by 2005. It has been negative since then (Figure 5.2b).

Japanese banks were not able to compensate for the decrease in interest margins by boosting the lending volumes. Therefore, the banks' net interest income substantially declined, which in turn depressed profits. Between 1999 and 2015, revenue from the traditional credit business decreased by 22 percent for large city banks, by 13 percent for tier-one regional banks, by 28 percent for tier-two regional banks, and by 25 percent for the shinkin banks (Figure 5.3).[5]

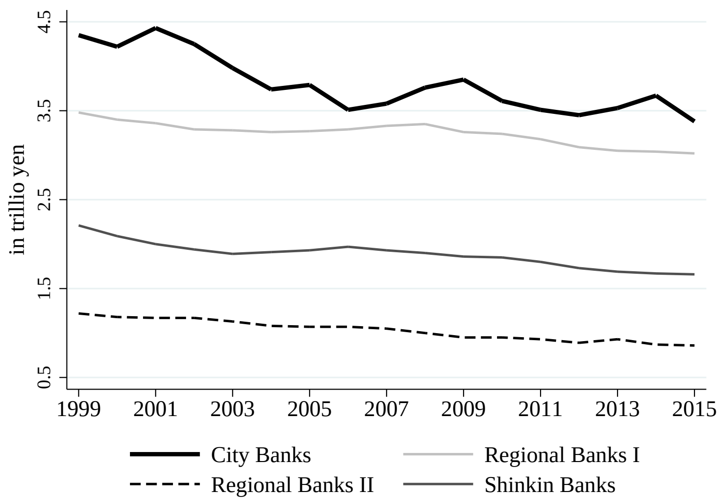
In addition to declining interest margins, Japanese banks incurred high losses through writing off non-performing loans. During the 1990s Japanese banks had been advised to keep bad loans in their balance sheets and to build respective provisions. However,

[4] The Bank of Japan cut the short-term interest rate from 6 percent in 1991 to 0 by March 1999. The size of the balance sheet of the Bank of Japan increased from 18 percent of GDP in January 1999 to 95 percent by the end of 2016, due to extensive bond purchases, particularly government bonds.

[5] *City banks* are large commercial banks that operate at a national and international level and have branches in all major cities of Japan. *Tier-one regional banks* and *tier-two regional banks* are mainly active in retail banking and focus on specific regions (e.g. one prefecture). They mainly engage in lending to the corporate sector, specifically small and medium enterprises (approximately 70 percent of all loans are granted to SMEs). Tier-one and tier-two regional banks have different histories. Therefore, statistics of the Japanese Bankers Association are aggregated in two different categories. Since the financial market liberalizations in the 1990s the business model of both groups is mainly the same. Today, the main difference between the two groups is that tier-two regional banks are significantly smaller. *Shinkin banks* are credit associations operating within a prefecture, managing deposits and providing loans to and from their owners (mainly SMEs).

with the outbreak of the Japanese financial crisis, the strategy towards the problem of bad loans changed. From 2002 onwards the Financial Revitalization Program urged banks to resolve the provisions and to write off the bad loans.[6] The realized losses constituted an additional burden for Japanese banks until the start of the Abenomics. These losses had to be compensated by additional revenues.

Figure 5.3: Net Interest Income by Bank Type



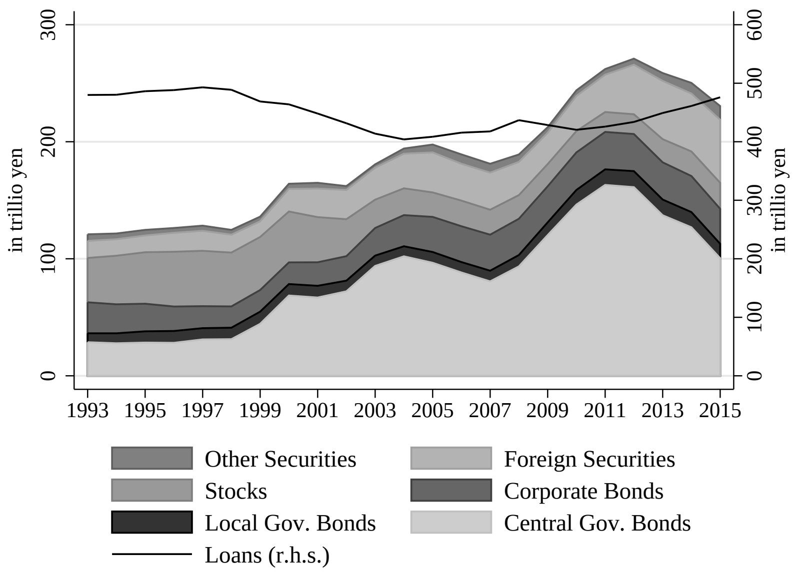
Source: Japanese Bankers Association, Shinkin Central Bank. Net interest income defined as interest income minus interest expenses.

5.2.2 Alternative Sources of Income

Additional revenue was initially generated by the substitution of credit to the private sector by the purchase of central and local government bonds. This became possible because general government debt, as a share of gross domestic product (GDP), increased from 70 percent in 1990 to 250 percent in 2016. From 1999 to 2012, the share of government bonds in total assets increased from 5 percent to 27 percent for city banks, from 8 percent to 17 percent for tier-one regional banks, from 5 percent to 15 percent for tier-two regional banks and from 12 percent to 25 percent for shinkin banks. Figure 5.4 shows the composition of investment securities.

[6] Between 1999 and 2014, the overall volume of write-offs of bad loans by Japanese banks was equivalent to 18 trillion yen. Of this, city banks wrote off 12.5 trillion yen, tier-one regional banks 5.6 trillion yen, and tier-two regional banks 0.6 trillion yen (Source: Japan Deposit Insurance Corporation). This process was supported by recapitalizations equivalent to 13 trillion yen (111 billion USD).

Figure 5.4: Composition of Investment Securities - all Banks (1993-2015)



Source: Bank of Japan.

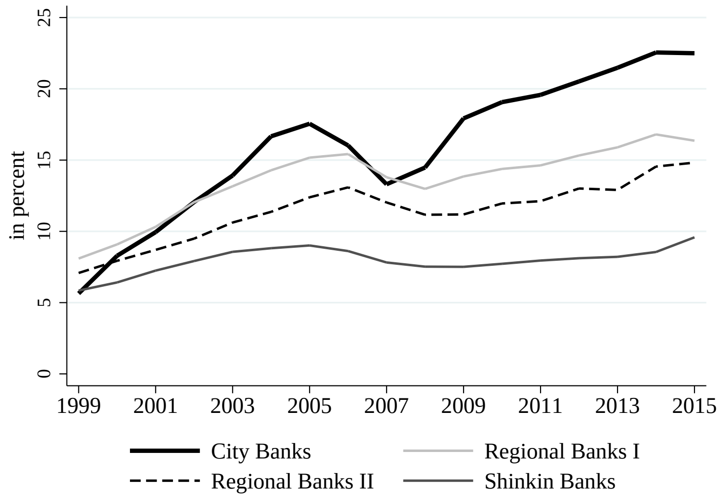
The purchases of government bonds were lucrative until the start of the Abenomics. The shift in the Bank of Japan's monetary policy towards aggressive quantitative easing in 2013, however, made government bond yields more volatile and pushed them into negative territory. As a result, banks strongly reduced their holdings of government bonds. By the end of 2015, the share of government bonds in total assets had declined to 9 percent for city banks, 13 percent for tier-one regional banks and 10 percent for tier-two regional banks. The decline in government bonds on the balance sheets was less pronounced for regional banks compared with city banks, because regional banks have (to date) held relatively large amounts in local government bonds that are less purchased by the Bank of Japan. For shinkin banks, the decline in central government bond holdings has been widely compensated for by purchases of local government bonds (Bank of Japan, 2016).

Given their declining income from traditional banking business, Japanese banks had little choice but to generate higher revenues through fees and commissions. The financial deregulation in the late 1990s ('Big Bang') paved the way for diversifying into new business areas.[7] Japanese banks developed new financial services and

[7] The Financial Services Agency's guidelines state that this includes consultations and support in connection with business matching and mergers and acquisitions (Ishikawa et al., 2013).

formed business alliances with non-bank companies.[8] Banks expanded their sales of investment trusts and private pension policies to households, and increased their corporate customer fees – for example, fees for arranging syndicated loans and sales of derivatives to firms (Bank of Japan, 2005).

Figure 5.5: Fees and Commissions as Share of Ordinary Income by Bank Type



Source: Japanese Bankers Association, Shinkin Central Bank.

Regional banks and shinkin banks ceased to follow a purely lending-based business model to embrace a more service-oriented business model. These banks started to provide services to corporate customers, to resolve challenges such as establishing new business relationships, exploring new markets or finding business successors (Ishikawa et al., 2013). As a result, revenues from fees and commissions, as a share of total ordinary income, significantly increased across all types of banks (Figure 5.5). The highest increase has been realized by the large city banks, which became strongly involved in the investment business and profited from having large, export-oriented enterprises as customers.

[8] In the early 2000s, Japanese banks increased their business alliances with securities and insurance companies, and entered into consumer finance through joint ventures or partnerships with consumer finance companies. Cooperating with firms that have physical or electronic networks (e.g. railway and mobile phone companies), banks started to offer new financial services – such as small-value payments (Bank of Japan, 2006).

5.2.3 Adjustment of Costs

Depending on their ability to compensate for declining revenues from traditional banking business by instituting new sources of income, Japanese banks had to cut their general and administrative expenses. The pressure to cut costs was stronger for the small shinkin banks and tier-two regional banks than it was for the larger tier-one regional banks and city banks. Between 1999 and 2015, personnel expenses declined by 6 percent for city banks and by 12 percent for tier-one regional banks. In contrast, the tier-two regional banks reduced their personnel expenses by 25 percent and the shinkin banks by as much as 35 percent. A similar pattern evolved with respect to non-personnel expenses, which even increased by 8 percent for city banks and fell only by 3 percent for tier-one regional banks. Non-personnel expenses dropped by 16 percent for tier-two regional banks and by 19 percent for shinkin banks.[9]

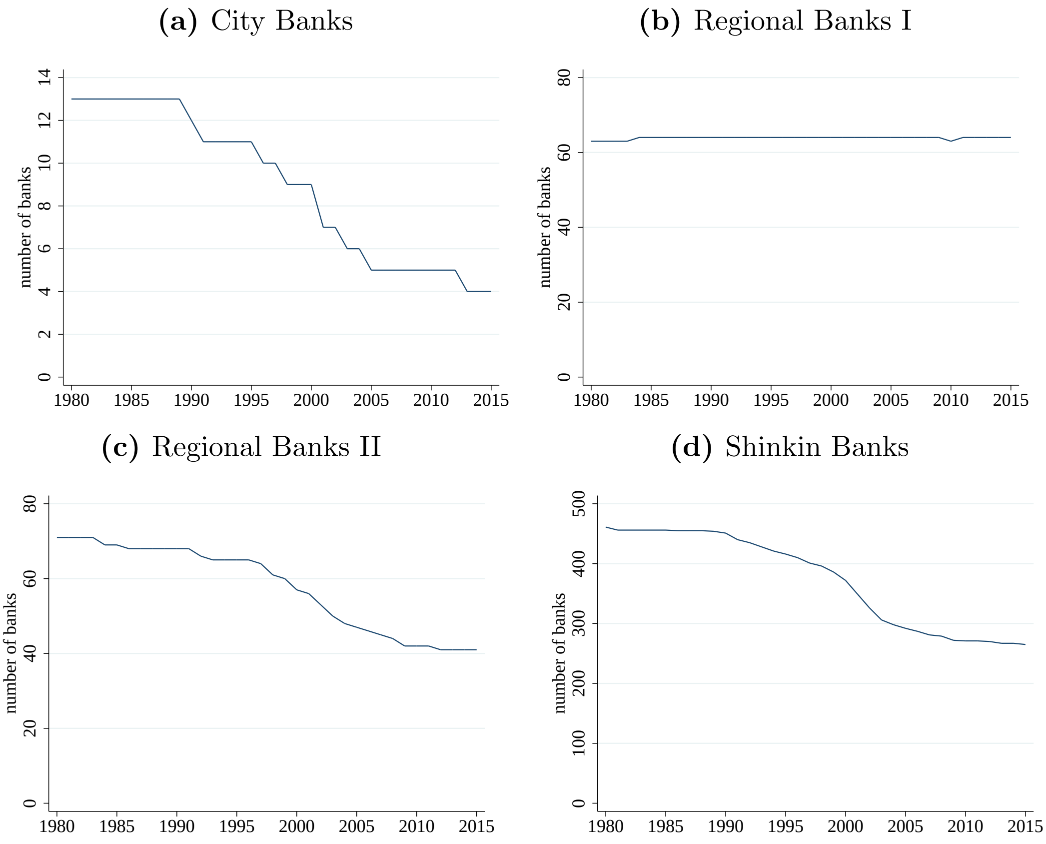
The pressure to reduce costs has accompanied a process of concentration in the Japanese banking sector through mergers and acquisitions. Hosono et al. (2009) argue that one motive for Japanese banks to engage in M&As was to increase efficiency. As a result, the number of Japanese financial institutions – including city banks, trust banks, tier-one regional banks, tier-two regional banks and shinkin banks – declined from 606 in 1990 to 379 in 2016 (JBA, 2017). As shown in Figure 5.6, the number of city banks has declined from 13 in 1990 to just five at present. While all tier-one regional banks have survived so far, the number of smaller tier-two regional banks has dropped from 68 in 1990 to 41 at present. The number of shinkin banks has also dropped, from 451 in 1990 to 265 in 2016.

Moreover, for all four bank types the number of branches has declined steadily since the mid-1990s (Figure 5.7a).[10] The reduction in the number of branches has been more severe for smaller banks (tier-two regional banks and shinkin banks) than for larger banks. A similar pattern has occurred with regard to the numbers of regular employees, which have been more drastically reduced in tier-two regional and shinkin banks than among other types of banks (Figure 5.7b). The substitution of regular employees by part-time employees allowed banks to adjust more easily to volatile business conditions.

[9] All data were provided by the Japanese Bankers Association and the Shinkin Central Bank.

[10] There is no distinction between branches with employees that provide all services – called 'branches' (shiten: 支店) or 'main branches' (honshiten: 本支店) – versus branches with limited services, in particular ATM machines (shu chou jo: 出張所). The sharp increase in the number of branches of city banks between 2015 and 2016 was the result of the extension of ATM corners by Mitsui-Sumitomo Bank, in areas where the Tokyo Olympics will take place.

Figure 5.6: Number of Banks (1980-2015)



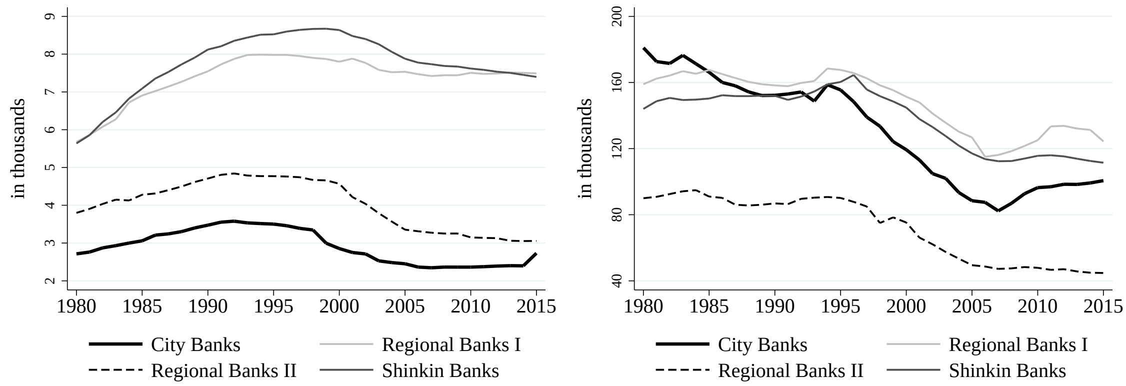
Source: Japan Financial Directory.

The continuing pressure on profits as a result of the Bank of Japan's low-interest rate policy suggests that Japanese banks' efficiency should have increased because of the concentration process in the banking sector and other adjustment measures of the banks. However, the simultaneous decline in competition as a result of increased concentration, combined with the persistent low-cost liquidity provision by the Bank of Japan, might have reduced the pressure on Japanese banks to increase their efficiency (Schnabl, 2015).[11] In addition, the squeezing of profits may have reduced the banks' resources for implementing measures to enhance their efficiency. Hence, the impact of Japanese monetary policy crisis management on banks' efficiency is ambiguous from a theoretical point of view.

[11] For instance, Hosono et al. (2009) provide evidence that M&As in the Japanese banking sector have not necessarily improved efficiency.

Figure 5.7: Consolidation Process in the Japanese Banking Sector

(a) Number of Branches | (b) Number of Regular Employees



Source: Japan Financial Directory.

5.3 Development of Bank Efficiency in Japan

As shown above, during the post-bubble period, the Bank of Japan's monetary policy has substantially changed the operating environment of Japanese banks. The gradual reduction in interest rates and the introduction of unconventional policy measures has eroded the banks' traditional sources of income. For banks to remain profitable in a low-interest rate environment, a more efficient utilization of resources is crucial.

5.3.1 Concept of Efficiency Measures

To evaluate the development of Japanese bank efficiency, we estimate for each bank i and each year t an output-oriented technical efficiency score, $TE_{i,t}$. This score reflects the bank's distance from a pre-specified benchmark, known as the efficiency frontier (Farrell, 1957).[12] Technical efficiency can be defined as a bank's ability to produce a maximum set of outputs (such as loans, securities and operating income) given a set of inputs (such as deposits, employees and branches). Farrell's (1957) output-oriented technical efficiency score equals 1 when the bank operates at the 'best practice' frontier. Higher values than unity indicate inefficiency.[13] Following Charnes et al. (1978) and Banker et al. (1984), we further decompose a bank's overall

[12] Farrell (1957) decomposes a firm's overall efficiency (or economic efficiency) in technical efficiency, reflecting a firm's ability to produce a maximum set of outputs from a given set of inputs, and price efficiency (or allocative efficiency), reflecting a firm's ability to choose an optimal set of inputs given respective prices. We focus on technical efficiency of Japanese banks as input prices were not available.

[13] For details see Appendix D.1.

technical efficiency score into pure technical efficiency ($PTE_{i,t}$) and scale efficiency ($SE_{i,t}$), with:

$$TE_{i,t} = PTE_{i,t} \times SE_{i,t} \tag{5.1}$$

The decomposition helps to identify whether Japanese banks' technical inefficiencies are the result of inefficient operations (measured by $PTE_{i,t}$) or alternatively from not operating at an optimal scale (measured by $SE_{i,t}$), or both. We are furthermore able to determine if Japanese banks are operating under increasing, decreasing or constant returns to scale – hence whether banks are operating below, above or at their technically optimal scale.[14] Prior studies on the Japanese banking sector indicate that pure technical inefficiencies are more severe than scale inefficiencies, as Japanese banks have been following a gradual consolidation process ever since the bubble economy burst (Fukuyama, 1993; McKillop et al., 1996; Drake and Hall, 2003; Azad et al., 2014).

A common method employed to compute efficiency scores is the Data Envelopment Analysis (DEA). This method measures efficiency as 'relative to a non-parametric, maximum likelihood estimate of an unobserved true frontier, conditional on observed data [...]' (Simar and Wilson, 2007, p.32). The DEA method is a flexible non-parametric approach that does not require a specific functional form of a bank's production function. However, the downside is that DEA does not allow for random errors and is therefore sensitive to random variations in the data. As the method has no statistical foundation, the estimates cannot be assessed for statistical significance (Coelli et al., 2005). We work around this problem by using the bootstrap approach of Simar and Wilson (1998, 1999), which enables the statistical properties of non-parametric estimators of banks' efficiency to be estimated. This allows us to obtain bias-corrected efficiency scores.[15]

5.3.2 Input and Output Data

In modelling banks' production function, we follow the intermediation approach of Sealey and Lindley (1977) which considers banks as institutions that transform deposits into loans and other earning assets, using labour and physical capital as

[14] Increasing (decreasing) returns to scale indicate that the bank is too small (large).
[15] For more information on DEA, see Appendix D.2. For more information on the bootstrap approach of Simar and Wilson (1998, 1999), see Appendix D.3.

inputs.[16] This is in line with previous studies of the Japanese banking sector (e.g. Fukuyama, 1993; Drake and Hall, 2003). The banks' activities are modelled in a three-input and two-output framework.

Following Assaf et al. (2011) and Fukuyama and Weber (2009), the inputs are total deposits and short-term borrowed funds (X1), physical capital (land, premises and fixed assets) (X2), and labour (number of employees) (X3). The outputs are total loans and bills discounted (Y1), and securities issued (Y2). The inputs and outputs (excluding employees) are measured in yen and deflated using the GDP deflator provided by the World Bank. Table 5.1 shows the descriptive statistics for inputs and outputs according to bank type.

Table 5.1: Descriptive Statistics of Inputs and Outputs

	CB	RB I	RB II	SB	Total
(X1) Deposits (billion yen)	57,479	3,212	1,305	377	1,929
(X2) Physical Capital (billion yen)	568	45	21	6	24
(X3) Employees (number of)	15,067	2,028	1,091	399	988
(Y1) Loans (billion yen)	3,5710	2,261	977	205	1,237
(Y2) Securities (billion yen)	17,130	976	313	110	569

Source: Bankscope, annual reports of individual banks, Nikkei NEEDS database, Japanese Bankers Association. Values indicate sample mean per bank type. CB: city banks, RB I: tier-one regional banks, RB II: tier-two regional banks, SB: shinkin banks.

To construct our dataset on Japanese banks, we use information drawn from financial statements of individual banks provided by the BankScope database. Our dataset is completed using data from the annual reports of individual banks, the Nikkei NEEDS database and information from the Japanese Bankers Association. Our final dataset for the efficiency analysis comprises 6,183 observations from 401 Japanese banks for the financial years 1999 to 2015. Our sample covers almost the full spectrum of bank types operating in Japan: it includes 16 city banks, 64 tier-one regional banks, 41

[16] In contrast, the production approach assumes that banks primarily produce services for their account holders (Benston and Smith, 1976).

tier-two regional banks and 280 shinkin banks.[17] The breakdown of the sample is shown in Table 5.2.[18]

Table 5.2: Sample Structure of Efficiency Analysis

	CB	RB I	RB II	SB	Total
1999	9	48	26	254	337
2000	9	48	28	255	340
2001	7	48	32	266	353
2002	7	56	36	269	368
2003	7	58	38	271	374
2004	7	62	40	272	381
2005	6	62	40	272	380
2006	6	62	40	271	379
2007	6	61	39	271	377
2008	6	59	37	269	371
2009	6	61	37	269	373
2010	6	61	37	268	372
2011	6	61	40	267	374
2012	6	62	41	269	378
2013	5	61	39	267	372
2014	5	59	38	263	365
2015	5	57	37	190	289

Notes: CB: city banks, RB I: tier-one regional banks, RB II: tier-two regional banks, SB: shinkin banks.

5.3.3 Efficiency Scores Results

Table 5.3 summarizes the annual mean efficiency scores for the Japanese banking sector over the period 1999–2015 as compiled by DEA.[19] Columns (1) to (3) list the average bias-corrected technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) estimates. Columns (4) to (6) summarize the share of banks operating under increasing (IRS), constant (CRS) or decreasing returns to scale (DRS).

[17] Our analysis differs from other studies on Japanese bank efficiency to the extend that our sample contains both commercial banks (city banks and regional banks) and cooperative banks (shinkin banks). Fukuyama and Weber (2009) and Assaf et al. (2011) estimate efficiency scores only for shinkin banks. Altunbas et al. (2000) and Drake and Hall (2003) focus only on commercial banks. Separate estimations for commercial banks and cooperative banks, however, only allow a comparison between banks of the same ownership type. Altunbas et al. (2001) argue that a combined estimation permits a comparison between the different types of banks relative to the industry 'best practice' frontier. Other efficiency studies analysing both commercial and cooperative banks include for instance Altunbas et al. (2001) and Weil (2004). Fukuyama and Weber (2008) combine both regional and shinkin banks in their efficiency analysis on Japanese banks.

[18] Total numbers differ from the annual numbers in Table 5.2 due to the different participation behaviour of banks in our sample. Banks which were involved in M&As are pre-merger treated as separate entities.

[19] We used the FEAR software by Wilson (2008) to obtain the bias-corrected efficiency scores.

Table 5.3: Annual Mean Efficiency Scores of All Banks (1999-2015)

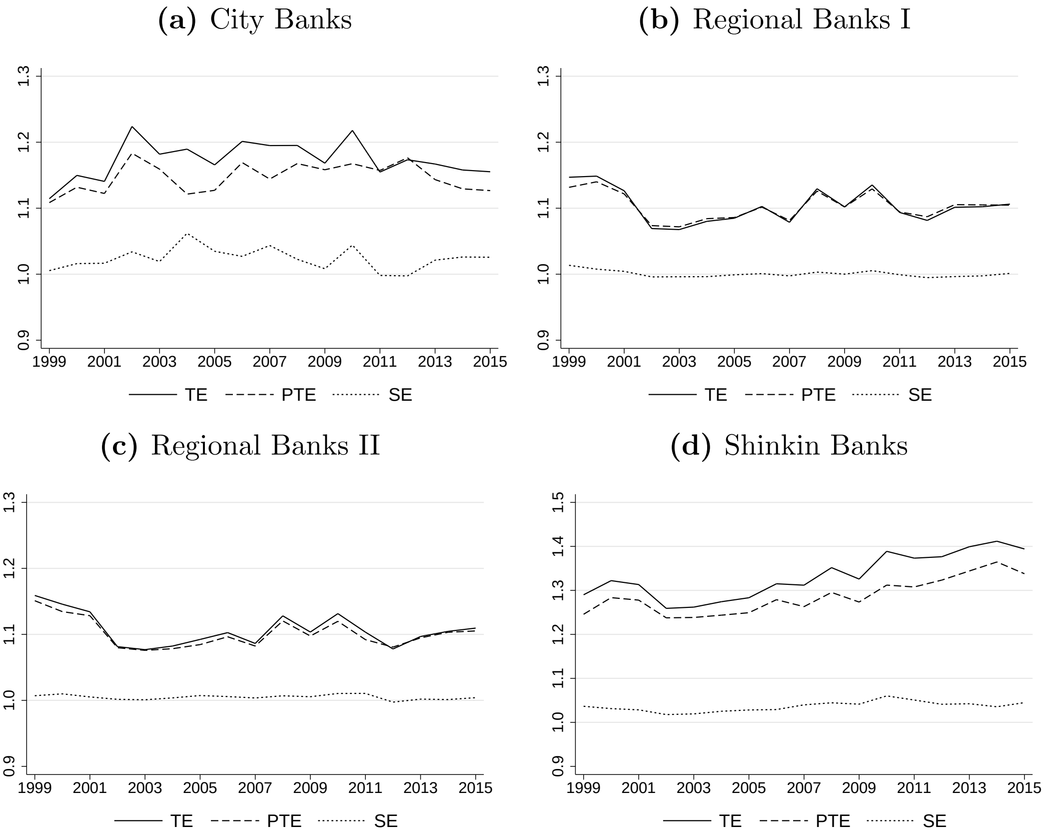
	(1) TE	(2) PTE	(3) SE	(4) IRS	(5) CRS	(6) DRS
1999	1.255	1.219	1.030	0.91	0.04	0.05
2000	1.279	1.247	1.026	0.86	0.04	0.10
2001	1.268	1.240	1.023	0.89	0.06	0.05
2002	1.212	1.196	1.013	0.88	0.05	0.07
2003	1.212	1.195	1.014	0.87	0.04	0.09
2004	1.221	1.198	1.019	0.90	0.04	0.06
2005	1.229	1.203	1.021	0.91	0.04	0.06
2006	1.256	1.229	1.022	0.92	0.03	0.04
2007	1.249	1.213	1.029	0.92	0.05	0.03
2008	1.292	1.249	1.034	0.91	0.04	0.06
2009	1.265	1.226	1.031	0.89	0.03	0.08
2010	1.319	1.261	1.046	0.91	0.03	0.06
2011	1.295	1.247	1.037	0.95	0.03	0.02
2012	1.293	1.256	1.028	0.88	0.05	0.07
2013	1.316	1.276	1.030	0.92	0.03	0.04
2014	1.326	1.292	1.026	0.86	0.05	0.08
2015	1.297	1.258	1.031	0.81	0.06	0.13
Mean	1.269	1.235	1.027	0.89	0.04	0.06

Notes: Bias-corrected values based on the bootstrap procedure. TE is the technical efficiency score. PTE is the pure technical efficiency score. SE is the scale efficiency score. Values above unity indicate inefficiencies. IRS/CRS/DRS are the shares of banks operating under increasing/ constant/ decreasing returns to scale, respectively.

Table 5.3 provides evidence that the Japanese banking sector experienced large inefficiencies across all sampled years. Relative to the constructed frontier, the average technical efficiency for all banks in our sample was around 1.27. Hence, Japanese banks could have increased their output by around 27 percent had the inputs been used the most efficient way. Over time the average technical efficiency of the Japanese banking sector increased considerably between 2000 and 2004, but deteriorated thereafter. Technical efficiency in particular has declined since 2010, especially after the introduction of Abenomics in 2013.

The mean pure technical efficiency score was 1.24, explaining the largest share of Japanese banks' technical inefficiencies. This score implies that the output of the Japanese banking sector could have been 24 percent higher if banks had operated at the PTE frontier. Scale inefficiencies have been rather small, at an average of only 1.027. Thus, banks could have increased their output by only 2.7 percent if they had operated at an optimal scale. However, scale inefficiencies have been increasing since around 2007 despite an acceleration of the concentration process. According to the efficiency measure we used, 90 percent of the banks have operated under increasing returns to scale (i.e. below their optimal scale). This finding implies a further concentration potential. Only 6 percent or so have operated under decreasing returns to scale. These findings suggest that although the consolidation process in the Japanese banking sector has advanced since the 1990s, scale inefficiencies have not been resolved.

Figure 5.8: Annual Efficiency Scores by Bank Type (1999-2015)



Notes: Bias-corrected values based on the bootstrap procedure. TE is the technical efficiency score. PTE is the pure technical efficiency score. SE is the scale efficiency score. Values above unity indicate inefficiencies.

Figure 5.8 shows the efficiency score estimates between 1999 and 2015 by bank type.[20] City banks exhibited rather large technical inefficiencies compared with both types of regional banks. With an average technical efficiency score of 1.172 during the sample period, city banks could have increased their output by around 17.2 percent. Over time the efficiency development of city banks has been rather unsteady, with periods of significantly declining overall technical efficiency (e.g. 1999-2002, 2006, 2010) followed by periods of improvement (e.g. 2003-2005, 2006-2009, 2012-2015). Overall, technical efficiency and both components decreased between 1999 and 2015. The mean scale efficiency score was 1.024, with an average 40 percent of city banks

[20] For a more detailed overview of the results, see Table D.1 to Table D.4 in Appendix D.5.

operating under decreasing returns to scale – thus *above* their optimal scale. Our findings hence imply that the consolidation of city banks into so-called 'mega banks' has not necessarily increased their pure technical and scale efficiency.

Tier-one and tier-two regional banks have been – on average – the most efficient banks according to our measures. Both of these bank types attained a mean technical efficiency score of 1.10 for our observation period. For both types, scale inefficiencies have been rather small, such that any further consolidation among regional banks cannot be expected to considerably improve their efficiency through scale effects. Furthermore, we find for both types of regional banks that pure technical efficiency increased considerably between 1999 and 2003 and has slightly decreased since 2003.

Shinkin banks exhibited by far the largest inefficiencies relative to the industry's 'best practice' frontier, with an average technical efficiency score of 1.33. Technical inefficiencies increased from 1.29 in 1999 to 1.39 in 2015, despite a substantial consolidation process. Shinkin banks' inefficiencies are mainly driven by pure technical inefficiencies; however, scale inefficiencies are also larger than that of other bank types. The average scale efficiency score for shinkin banks is 1.035. According to the efficiency measure, roughly 96 percent of shinkin banks have operated below their optimal scale, meaning they are too small. Our findings of relatively large technical inefficiencies among shinkin banks is in line with previous efficiency studies and can be attributed to factors such as high amounts of non-performing loans, poor restructuring, the lack of market power and management failings (Assaf et al., 2011).

Summing up the results of our efficiency analysis, we find that despite their efforts to cut costs and improve efficiency through gaining economies of scale or scope, Japanese Banks' technical inefficiencies could not be resolved in our observation period. Pure technical efficiencies and scale inefficiencies persist in the Japanese banking sector.

5.4 Adjustment Measures as Drivers of Japanese Bank Efficiency

Based on the efficiency measures compiled above, we trace the determinants of the banks' inefficiencies since the 1998–99 Japanese financial crisis. In particular, we control for the impact of the Bank of Japan's monetary policy and the banks' strategies to cope with the low-interest rate environment.

5.4.1 Estimation Framework and Methodology

To identify the sources of Japanese banks' inefficiencies, we regress the efficiency estimates (described in Section 5.3) on a set of explanatory variables.[21] We estimate the following model:

$$\hat{\theta}_{i,t} = \beta_0 + \beta_1 z_{i,t} + \delta_t + \epsilon_{i,t} \tag{5.2}$$

where the dependent variable $\hat{\theta}_{i,t}$ is the estimated efficiency score of bank i at time t. In our analysis we run equation (5.2) for both the estimated technical efficiency ($\widehat{TE}_{i,t}$), as well as pure technical efficiency scores ($\widehat{PTE}_{i,t}$) as dependent variables.[22] The vector $z_{i,t}$ represents a matrix of explanatory variables, including those commonly mentioned in the literature as having a significant impact on bank efficiency, as well as variables reflecting Japanese banks' adjustment strategies to the Bank of Japan's monetary policy as described in Section 5.2. Furthermore, we control for year fixed effects δ_t. The term $\epsilon_{i,t}$ is the idiosyncratic error term, assumed to be identically and independently distributed.

To estimate equation (5.2) we use the bootstrapped truncated regression model proposed by Simar and Wilson (2007).[23] Given the bounded nature of the estimated efficiency scores from $\widehat{TE}_{i,t} \geq 1$ and $\widehat{PTE}_{i,t} \geq 1$, a truncated regression model leads to more consistent and accurate estimates than Tobit or OLS models, which have traditionally been used in two-stage efficiency studies of the banking sector (e.g. McKillop et al., 2002; Fukuyama and Weber, 2009).

5.4.2 Variable Definition

The data basis for our regression analysis is the dataset presented in Section 5.3.2. Owing to missing data, the sample for our regression analysis is slightly smaller than the original sample, and comprises 5,823 observations from 389 banks. Descriptive statistics of all explanatory variables are shown in Table 5.4.

Control variables that were found to have a significant impact on Japanese bank efficiency are market share (MS), non-performing loans (NPL), return on average

[21] For more information and an overview of efficiency studies using a two-stage approach, see Simar and Wilson (2007). Studies on the Japanese banking sector using a two-stage approach include Altunbas et al. (2000), Fukuyama and Weber (2009) and Assaf et al. (2011).

[22] We omit $\widehat{SE}_{i,t}$ from our regression analysis as a bank's scale efficiency is the quotient of $\widehat{TE}_{i,t}$ and $\widehat{PTE}_{i,t}$ and is determined by the bank's size. This is in line with previous studies.

[23] For more information see Appendix D.4.

assets ($ROAA$) and bank size (Fukuyama and Weber, 2009; Assaf et al., 2011). Market share is proxied by the ratio of deposits of bank i to total banking sector deposits; previous studies showed that the market share has a positive impact on efficiency (Fukuyama and Weber, 2009). Non-performing loans are measured by risk-monitored loans divided by total loans. Non-performing loans are expected to have a negative impact on Japanese bank efficiency, as evidenced by previous studies (Altunbas et al., 2000). Furthermore, we expect the return on average assets to be positively correlated with bank efficiency (Assaf et al., 2011).

Table 5.4: Descriptive Statistics for Variables in the Regression Analysis

	Mean	SD	Min	Max
$\widehat{\text{TE}}$	1.25	0.16	1.00	2.22
$\widehat{\text{PTE}}$	1.21	0.14	1.00	2.16
MS	0.17	0.66	0.01	17.22
NPL	7.45	4.10	0.00	37.35
ROAA	0.09	0.45	-7.24	2.07
NIM	1.71	0.38	0.10	3.51
SECLOAN	0.51	0.28	-0.01	2.95
GOVSEC	0.38	0.21	-0.07	8.28
NIOI	0.07	0.47	-12.37	28.66

To control for the impact of the Bank of Japan's monetary policy, we include the net interest margin (NIM), defined as a bank's net interest revenue as share of its average total earning assets (in percent). Whereas the net interest margin is traditionally regarded as reflecting asset productivity (e.g. Assaf et al., 2011), we use it as an indicator of a bank's exposure to the low-interest rate environment and unconventional monetary policy.[24] A positive coefficient of NIM in our estimation model would imply that an increase in the net interest margin would lower efficiency (i.e. increase inefficiency).[25] A decline in net interest margins – as it occurred in our observation period – would thus have had a positive impact on Japanese banks' efficiency.[26] In contrast, a negative coefficient implies that an increase in the net interest margin would increases technical efficiency (i.e. reduce inefficiency).

[24] Busch and Memmel (2015) and Claessens et al. (2017) show empirically that banks' net interest margins significantly react to changes in interest rates triggered by central banks.

[25] Higher values of $\widehat{TE}_{i,t}$ and $\widehat{PTE}_{i,t}$ indicate lower efficiency and higher inefficiency.

[26] Analysing the efficiency of shinkin banks, Fukuyama and Weber (2009) find that technical efficiency decreases as the net interest margin increases. Fukuyama and Weber (2008) argue '[...] that the cooperative nature of these banks allows managers to engage in expense-preference behaviour. Higher net interest margins might thus offer sufficient cushion to allow managers to indulge in such behaviour, rather than pursue efficiency with greater effort' [p.285]. A decline in margins might thus incentivize banks to increase efficiency to mitigate a loss in revenue.

Declining net interest margin would thus be associated with a loss in efficiency, either because the bank is less able or willing to increase efficiency.

As discussed in Section 5.2, Japanese banks have increasingly invested in securities – particularly government bonds – and have raised the share of non-interest income (fees and commissions). As proxies for changes in the bank's portfolio mix, we include the securities-to-loan ratio ($SECLOAN$) and the share of government securities among total securities ($GOVSEC$). The ratio of non-interest operating income to total operating income ($NIOI$) is meant to capture the effect of banks' efforts to diversify their revenue structure. The impact of a bank's diversification strategy on its efficiency is theoretically ambiguous.[27]

Bank size is captured by a set of dummy variables to allow for non-linearities in the relationship between efficiency and bank size, with thresholds chosen following Berger and Mester (1997). The definitions of small, medium, large and huge banks, and the distribution across the bank types, are shown in Table 5.5. We assume that there is no clear link between bank size and efficiency.[28] Furthermore, we control for the distinct organizational and governance characteristics of banks by including dummies for each bank type (CB, city banks; $RB\,I$, tier-one regional banks; $RB\,II$, tier-two regional banks; SB, shinkin banks).[29]

Table 5.5: Bank Size Dummy Variables

	Definition	CB	RB I	RB II	SB
SMLBANK	TA<114 billion yen	0%	0%	0%	23%
MEDBANK	114 billion yen≤TA<1.14 trillion yen	0%	13%	54%	70%
LARBANK	1.14 trillion yen≤TA<11.14 trillion yen	20%	86%	46%	7%
HUGBANK	11.14 trillion yen≥TA	80%	1%	0%	0%

Notes: 114 billion yen equal around 1 billion USD. TA: total assets, CB: city banks, RB I: tier-one regional banks, RB II: tier-two regional banks, SB: shinkin banks.

[27] A higher share of securities can have a positive impact on a bank's efficiency, because securities investment is associated with lower operating costs than the provision of loans as the latter involves evaluation and monitoring activities (Sarmiento and Galán, 2015). However, simultaneously the expansion of non-interest income by providing more fee-based services and products involves more resources. Therefore, an adjustment of a bank's revenue structure might be associated with decreasing efficiency.

[28] For a sample of Japanese commercial banks, Altunbas et al. (2000) identify a positive impact of size, measured by total assets, on efficiency. However, for Japanese shinkin banks, Fukuyama and Weber (2009) find a negative relationship between size and bank efficiency.

[29] The bank-size dummy thresholds are chosen in a way that avoids a multi-collinearity problem with bank-type dummies. All bank types include at least two different size groups.

5.4.3 Estimation Results

Table 5.6 reports the estimation results of equation (5.2) for both $\widehat{TE}_{i,t}$ and $\widehat{PTE}_{i,t}$ scores as dependent variables.[30] Column (1) and (3) show the results for a model including the explanatory variables which are usually used in the literature. Column (2) and (4) extend the estimation models by including variables that may influence a bank's efficiency in a low-interest-rate and unconventional monetary policy environment. This includes the net-interest margin, the securities to loan ratio, the share of government bonds and the ratio of non-interest operating income to total operating income. In addition, dummies for bank size and bank type are included.

Our results show that all traditional control variables (MS, NPL, $ROAA$) are statistically significant with the expected sign, apart from the coefficient of $ROAA$ which is not statistically significant in the extended model. The results confirm findings of previous studies that a higher market share increases efficiency. Furthermore, a higher non-performing loan ratio is linked to a lower degree of efficiency. The negative coefficient of $ROAA$ implies that a higher return on average assets is linked to a higher degree of efficiency.

Our results also show that the net interest margin has a statistically significant effect on bank efficiency. The negative coefficient implies that a higher net interest margin increases both technical and pure technical efficiency. The decline in banks' net interest margin – as it occurred in our sample period – can thus be interpreted as having impeded Japanese banks' efficiency development. The effect is rather large. Ceteris paribus, a 1-percentage-point decline in the net interest margin increases a bank's pure technical efficiency score by around 0.26 points, which captures a significant decline in efficiency. This may indicate one of two things: (1) depressed competition owing to consolidation in the banking sector, and/or the provision of low-cost liquidity by the Bank of Japan, have reduced the pressure on banks to improve their efficiency, or (2) the loss in banks' traditional source of income has constrained their ability to improve their efficiency. Either way, declining short- and long-term interest rates are clearly linked to a decline in Japanese bank efficiency.

Shifting their portfolio from loans to securities has helped Japanese banks to mitigate the negative impact on efficiency. A higher securities to loan ratio is associated with higher technical efficiency as well as higher pure technical efficiency

[30] Estimated using the simarwilson STATA command by Tauchmann (2016).

Table 5.6: Estimation Results

	(1) TE	(2) TE (ext.)	(3) PTE	(4) PTE (ext.)
MS	-0.0468***	-0.0501***	-0.0665**	-0.1603***
	[0.0162]	[0.0174]	[0.0291]	[0.0346]
NPL	0.0036***	0.0047***	0.0027***	0.0050***
	[0.0006]	[0.0006]	[0.0006]	[0.0006]
$ROAA$	-0.0255***	-0.0056	-0.0160***	0.0046
	[0.0052]	[0.0049]	[0.0054]	[0.0050]
NIM		-0.2173***		-0.2565***
		[0.0095]		[0.0089]
$SECLOAN$		-0.2378***		-0.1741***
		[0.0089]		[0.0092]
$GOVSEC$		-0.0356***		-0.0168*
		[0.0111]		[0.01010]
$NIOI$		-0.0031		-0.0046
		[0.0042]		[0.0040]
$MEDBANK$	-0.0251***	-0.0418***	0.0822***	0.0626***
	[0.0053]	[0.0051]	[0.0059]	[0.0054]
$LARBANK$	-0.0722***	-0.1150***	0.0705***	0.0474***
	[0.0107]	[0.0108]	[0.0115]	[0.0118]
$HUGBANK$	-0.0883	-0.1238**	0.0975	0.1586*
	[0.0741]	[0.0643]	[0.0860]	[0.0866]
RBI	-0.3006***	-0.2286***	-0.2637***	-0.2446***
	[0.0652]	[0.0588]	[0.0683]	[0.0683]
$RBII$	-0.2748***	-0.1691***	-0.2417***	-0.1931***
	[0.0660]	[0.0616]	[0.0695]	[0.0705]
SB	0.0923	0.2036***	0.0949	0.1209*
	[0.0650]	[0.0601]	[0.0695]	[0.0712]
Constant	0.1408***	0.1271***	0.1289***	0.1171***
	[0.0018]	[0.0015]	[0.0017]	[0.0015]
Observations	5,823	5,219	5,618	5,032

Notes: $\widehat{TE}_{i,t}$ and $\widehat{PTE}_{i,t}$ are the dependent variables. All models estimated using a truncated regression model. Negative coefficients indicate positive effect on efficiency and vice versa. Reference categories are $SMLBANK$ and CB. Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

(negative coefficients, significant at the 1-percent level). Moreover, a higher share of government securities seems to have additionally boosted efficiency (negative coefficients, significant at the 1-percent level). This supports our assumption that in an environment of low private-sector loan demand – and therefore increasing competition in the loan market[31]a switch to lending to the public sector (which is less resource-consuming) has been lucrative for Japanese banks. Furthermore, we find that the coefficient of non-interest operating income is negative for both technical efficiency and pure technical efficiency, but statistically not significant.[32]

The results with respect to the effect of bank size on efficiency are ambiguous. Small banks are used as a reference group. For technical efficiency, all coefficients for medium-sized, large and huge banks are negative and mostly statistically significant. This suggests that a larger bank size is linked to higher technical efficiency.[33] However, the positive coefficients of the bank-size dummies in the PTE estimation models indicate that larger banks have higher pure technical inefficiencies than small banks. The reversal of the coefficient signs in the TE and PTE models can be explained by the existence of scale inefficiencies that are captured in the TE score, but not the PTE score. Our results thus imply that positive scale-efficiency effects of larger size over-compensate the negative size-effects on pure technical efficiency. These findings suggest that the ongoing consolidation process in the Japanese banking sector has reduced scale inefficiencies by increasing the size of banks, but that this had the adverse side effect of increasing pure technical inefficiencies.

Furthermore, our estimation results confirm the findings reported in Section 5.3 concerning the efficiency differences between the types of banks. With city banks used as a reference group, tier-one regional banks emerge as the most efficient type. This applies to both technical and pure technical efficiency (largest negative coefficients, significant at the 1-percent level). In addition, tier-two regional banks show a higher technical and pure technical efficiency than city banks, although the gap is smaller than for tier-one regional banks. In contrast, shinkin banks exhibit larger technical and pure technical inefficiencies than any other type of bank. However, the coefficient is statistically significant for only two out of four specifications.

To check whether our results are robust to different sampling of the baseline dataset that we use for the computation of the efficiency scores, we re-estimate TE, PTE and

[31] As of the beginning of the 2000s, competition among banks in the loan business intensified, putting lending rates under pressure and further lowering interest margins. City banks have expanded their lending activities to rural areas, whereas regional banks have expanded to urban areas. Some regional banks have set up branches in neighbouring prefectures or major cities (Bank of Japan, 2006, 2008, 2012).

[32] The negative coefficient is in line with findings of DeYoung (1994) for commercial banks in the U.S.

[33] The negative coefficients of $MEDBANK$, $LARBANK$ and $HUGBANK$ mean that technical inefficiencies are lower compared with the reference category $SMLBANK$.

SE scores separately for two subgroups of banks: commercial banks (including city banks and both types of regional banks) and cooperative banks (including shinkin banks). We regress the newly compiled efficiency scores on the set of explanatory variables described above. The estimation results generally confirm the findings of our baseline regression.[34]

5.5 Conclusion

Since the bursting of the Japanese bubble economy, and increasingly since the Asian and Japanese financial crisis, Japanese banks have been under persistent pressure to adjust. We show that the Bank of Japan's crisis management helped to prevent a financial meltdown in the short term. However, the expansionary monetary policy has undermined the traditional source of income for Japanese banks, which previously strongly favoured credit provision to households and enterprises. Furthermore, it has become an important driving force for gradual consolidation within the Japanese banking sector, which has led to a drop in the number of banks, branches and regular employees. This trend suggests that the banks' efficiency should have improved due to gaining economies of scale.

However, our analysis provides evidence that the Bank of Japan's low-interest rate policy and unconventional monetary policy measures have contributed to declining efficiency in the Japanese banking sector. Despite substantial effort by banks to increase their efficiency, the erosion of traditional sources of income is identified as having triggered losses in technical efficiency. A lower degree of competition because of greater concentration, and the persistent provision of low-cost liquidity by the Bank of Japan might have contributed to the decline.

In particular, our analysis suggests that among city banks that have formed large financial conglomerates (so-called 'mega banks'), the concentration process seems to have gone too far and has therefore contributed to *reduced* efficiency. For small regional and shinkin banks, even a drastic consolidation process seems not to have been enough to achieve sufficient efficiency gains.

The announced continuation of the ultra-expansionary monetary policy by the Bank of Japan is likely to accelerate the concentration process among banks. This is because the interest rate margin can be expected to become further depressed, and

[34] See Appendix D.6 for a detailed discussion of the estimation results of the robustness check.

the role of public bonds as an instrument to stabilize profits will decline further. However, as our analysis has shown, concentration is accompanied by declining pure technical efficiency which is linked to welfare losses. Therefore, we recommend a gradual exit from ultra-expansionary monetary policy. This would ensure more efficient allocation of capital in the Japanese economy, based on competition among banks rather than low-cost liquidity provision by the central bank.

Appendix D

D.1 Estimating Efficiency Scores

We assume as set of banks each producing y outputs using x inputs. The production technology is described by S and models the transformation of inputs $x \in \mathbb{R}^N_+$, into outputs $y \in \mathbb{R}^M_+$. Hence, S models the set of all feasible input/output vectors:

$$S = \{(x, y) : x \text{ can produce } y\} \tag{D.1}$$

Farrell's (1957) output-oriented measure of technical efficiency models the maximum proportionate increase in output y for a given set of input x and technology S:[35]

$$\theta(x, y) \equiv sup\{\theta : (x, \theta y) \in S\} \tag{D.2}$$

where $\theta(x, y)$ being greater than or equal to 1. Note, that the Farrell output-oriented technical efficiency measure is equivalent to the reciprocal of Shephard's (1970) output distance function:

$$D_o(x, y) \equiv inf\{\theta : (x, y/\theta) \in S\} \tag{D.3}$$

with $D_o(x, y) \leq 1$ (Färe et al., 1985). Figure D.1 illustrates the technical efficiency concept for the one-input-one-output case using output-oriented measures. Banks A, B, C and D produce output y using input x and an unknown technology S. The line S_{CRS} represents the technology frontier assuming constant returns to scale. Following Farrell's (1957) definition, bank A is technically efficient as it lies at the technology frontier S_{CRS} and produces the optimal output y^*_A given input x_A. Banks B, C and D are technically inefficient as their outputs y_B, y_C and y_D are below their optimal output levels y^*_B, y^*_C and y^*_D. Farrell's (1957) output-oriented technical efficiency scores correspond to the ratios:

$$TE^{CRS}_B = 0y^*_B/0y_B \tag{D.4}$$

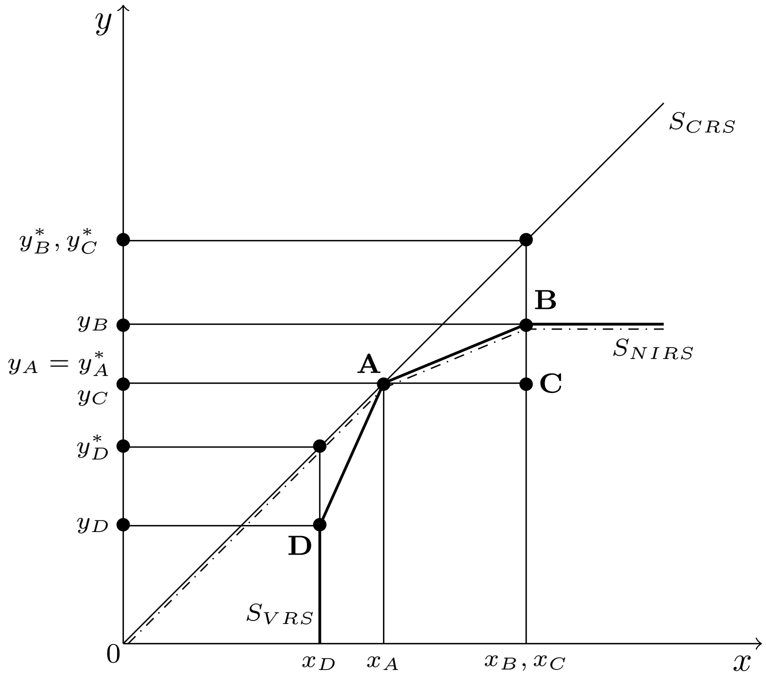
$$TE^{CRS}_C = 0y^*_C/0y_C \tag{D.5}$$

$$TE^{CRS}_D = 0y^*_D/0y_D \tag{D.6}$$

[35] Input-oriented efficiency measures focus on the optimal (i.e. minimal) set of inputs for a target output set.

The technical efficiency score $TE = 1$ if the bank operates at the best practice frontier, and $TE > 1$ if the bank exhibits technical inefficiency.

Figure D.1: Output-Oriented Technical Efficiency Measures



Notes: Illustration of output-oriented technical efficiency measure and components. Lines S_{CRS}, S_{VRS} and S_{NIRS} correspond to the constant returns to scale, variable returns to scale and non-increasing returns to scale production frontiers, respectively.

The assumption of a constant returns to scale technology frontier is only appropriate if all banks operate at an optimal scale. However, it can be shown that if banks are not operating at their optimal scale, the technical efficiency estimate is confounded by scale inefficiencies. Charnes et al. (1978) and Banker et al. (1984) extend the technical efficiency concept and propose a decomposition of TE into pure technical efficiency (PTE) and scale efficiency (SE) by relaxing the constant returns to scale assumption for the underlying technology:

$$TE = PTE \times SE \tag{D.7}$$

Assuming banks A, B, C and D are using a variable returns to scale technology,[36] as indicated in Figure D.1 by the S_{VRS} frontier, banks A, B and D would be technically efficient as all three are operating at the production frontier ($TE_A^{VRS} = TE_B^{VRS} = TE_D^{VRS} = 1$). However, banks B and D are technically inefficient as regards to the

[36] Variable returns to scale encompasses both decreasing as well as increasing returns to scale.

constant returns to scale frontier S_{CRS} ($TE_B^{CRS} > 1$ and $TE_D^{CRS} > 1$). The reason for the difference is that B and D are not operating at their optimal scale, hence they exhibit scale inefficiencies. TE^{VRS} can hence be regarded as measuring pure technical efficiency PTE. The scale efficiency measure corresponds to:

$$SE = \frac{TE^{CRS}}{TE^{VRS}} \tag{D.8}$$

As regards to our example illustrated in Figure D.1 the (overall) technical efficiency score (TE) the pure technical efficiency score (PTE) and the scale efficiency score (SE) of bank C correspond to:

$$TE_C = TE_C^{CRS} = 0y_C^*/0y_C \tag{D.9}$$

$$PTE_C = TE_C^{VRS} = 0y_B/0y_C \tag{D.10}$$

$$SE_C = 0y_C^*/0y_B \tag{D.11}$$

Although the scale efficiency score enables to determine whether scale inefficiencies exist or not, it does not indicate whether the bank is operating under increasing or decreasing returns to scale. To determine the nature of the scale inefficiencies a third technology frontier with the assumption of non-increasing returns to scale must be imposed (line S_{NIRS} in Figure D.1) and efficiency scores TE^{NIRS} estimated accordingly (Coelli et al., 2005; Banker et al., 1984). The nature of scale inefficiencies are determined by comparing TE^{NIRS} and TE^{VRS}. If $TE^{NIRS} = TE^{VRS}$ the bank exhibits decreasing returns to scale, if $TE^{NIRS} \neq TE^{VRS}$ it is operating under increasing returns to scale.[37] Referring to our example banks C and B display decreasing returns to scale and bank D increasing returns to scale.

D.2 Data Envelopment Analysis

The output distance functions $D_o^t(x_i^t, y_i^t)$ needed to construct technical efficiency scores can be estimated using either econometric or mathematical programming techniques with both differing in the way the efficiency frontier is estimated (Coelli et al., 2005). The former, known as *Stochastic Frontier Analysis*, is a parametric method that imposes a functional form on the production frontier and estimates

[37] Note that output- and input-oriented models may lead to different results in the findings of the nature of scale inefficiencies. See Golany and Yu (1997) for how to treat this problem.

econometrically the function's parameters. It is susceptible to misspecification. The second approach is a linear programming technique that constructs the efficiency frontier by enveloping input/output data of the decision making unit (DMU), with the non-parametric frontier being formed by the 'best practice' DMUs (Drake et al., 2006). The approach is referred to as *Data Envelopment Analysis* (Charnes et al., 1978).

The basic CRS output-oriented DEA model to estimate the relative efficiency at time t_1 can be described as follows. Assuming N inputs and M outputs for each bank i with $i = 1 \ldots, L$, the linear programming model is given by:

$$\begin{aligned}
&[D_o^{t1}(x_i^{t1}, y_i^{t1})]^{-1} = \max_{\theta_i \lambda_i} \theta \\
\text{s.t.:}\quad &\theta y_{im}^{t1} \leq \sum_{j=1}^{L} \lambda_j^{t1} y_{mj}^{t1}, \qquad && m = 1, \ldots, M, \\
&\sum_{j=1}^{L} \lambda_j^{t1} x_{nj}^{t1} \leq x_{in}^{t1}, && n = 1, \ldots, N, \\
&\lambda_i^{t1} \geq 0, && i = 1, \ldots, L.
\end{aligned} \tag{D.12}$$

where $x_i^{t1} = (x_{i1}^{t1}, ..., x_{in}^{t1}, ..., x_{iN}^{t1})' \in \mathbb{R}_+^N$ is the set of inputs for each bank i at time t and $y_i^{t1} = (y_{i1}^{t1}, ..., y_{im}^{t1}, ..., y_{iM}^{t1})' \in \mathbb{R}_+^M$ is the set of outputs; $\lambda_i^{t1} = (\lambda_1^{t1}, ..., \lambda_L^{t1})'$ is a vector of bank-specific weights conveying information on each bank's benchmark comparators.[38]

To estimate the scale efficiency score and to determine its nature the above described DEA model must additionally be run with (1) variable returns to scale and (2) non-increasing returns to scale imposed. Hence, the following additional restrictions must be included:

$$\sum_{j=1}^{L} \lambda_i^{t1} = 1 (\text{for VRS})$$

$$\sum_{j=1}^{L} \lambda_i^{t1} \leq 1 (\text{for NIRS})$$

[38] Note that an efficient bank i with $\theta_i = 1$ will be its own benchmark, hence λ_i includes only 0s except for a 1 in the ith position (Loukoianova, 2008).

D.3 Bootstrapping Efficiency Scores

Though the DEA method has been widely used in the empirical literature on efficiency, it suffers from the drawbacks of not allowing for random errors and having no statistical foundation (Coelli et al., 2005). To work around these problems Simar and Wilson (1998) introduced a statistical model that allows to determine statistical properties of DEA estimators in the multi-input and multi-output case by applying a bootstrapping procedure.[39] The basic idea of bootstrapping is to approximate the distribution of the true estimator is by constructing pseudo-samples and re-calculating the parameter of interest (Assaf et al., 2011). The re-sampling of the original data is based on assumptions of the true data-generating process and can be done directly from the original data (naïve bootstrap), or by employing a fitted model (smoothed bootstrap). The model developed by Simar and Wilson (1998) is based on the later. The bootstrap approach for efficiency scores can be summarized as follows:

1. Computation of efficiency scores θ_i for each DMU $i = 1, \ldots, L$ by solving the linear programming model as described above.
2. Generation of random sample of size L from $\{\hat{\theta}_i; i = 1, ..., L\}$ using kernel density estimation and reflection method as described by Silverman (1986), providing $\{\theta^*_{1b}, ..., \theta^*_{Lb}\}$.
3. Computation of a pseudo data set $\{(\mathbf{x}^*_{ib}, \mathbf{y}_i), i, ..., L\}$ where $\mathbf{x}^*_{ib} = \hat{\theta}_i/\theta^*_{ib}, i = 1, ..., L$ to form the reference technology.
4. Given this pseudo data set, computation of the bootstrapped efficiency scores $\hat{\theta}^*_{ib}$ of $\hat{\theta}_i$ for each $i = 1, \ldots, L$ by solving the bootstrap counterpart of the DEA model described above (i.e. inclusion of $\mathbf{x}^*_{ib}$).
5. Repetition of step 2 to 4 B times[40] to get for DMUs $i = 1, \ldots, L$ a set of bootstrap efficiency estimates $\hat{\theta}^*_{ib}, b = 1, \ldots, B$.

The computation of the bootstrap estimates allows making statistical inference on the efficiency scores, particularly, it allows for the construction of confidence intervals. The $(1-\alpha)$ confidence interval for each DMU is defined as:

$$\hat{\theta}_i + \hat{a}_\alpha \leq \theta_i \leq \hat{\theta}_i + \hat{b}_\alpha \tag{D.13}$$

[39] Bootstrapping was introduced by Efron (1979). For more information see Hall (1992) and Efron and Tibshirani (1993).

[40] Simar and Wilson (1998) suggest B=2000.

where $\hat{a}_\alpha$ and $\hat{b}_\alpha$ are computed following the procedure of Simar and Wilson (2000) by sorting $(\hat{\theta}^*_{ib} - \hat{\theta}_i)$ for $b = 1, \ldots, B$ in increasing order and deleting $(\frac{\alpha}{2} \times 100)$-percent of the elements at either side of the list. The values $-\hat{a}_\alpha$ and $-\hat{b}_\alpha$ are set equal to the endpoints of the sorted array.

Furthermore, it is possible to obtain bias corrections of the efficiency scores (e.g. Tortosa-Ausina et al., 2008). The bias of each efficiency estimation $\hat{\theta}_i$ can be calculated using the bootstrap sample, with the bias being defined as:

$$\widehat{\text{bias}_i}(\hat{\theta}_i) = \bar{\theta}^*_i - \hat{\theta}_i \tag{D.14}$$

with $\bar{\theta}^*_i = \frac{1}{B}\sum_{b=1}^{B} \hat{\theta}^*_i$. The bias-corrected estimator $\tilde{\theta}_i$ of each efficiency score θ_i is thus defined as:

$$\tilde{\theta}_i = 2\hat{\theta}_i - \bar{\theta}^*_i \tag{D.15}$$

D.4 Truncated Regression Model

In order to determine potential correlates of technical efficiency, the estimated efficiency scores $\hat{\theta}_i$ can be regressed on a set of explanatory variables z_i:

$$\hat{\theta}_i = z_i\beta + \epsilon_i \tag{D.16}$$

Simar and Wilson (2007) argue that the efficiency scores calculated using DEA suffer from strong correlation as the calculation of a given efficiency score depends on all other observations in the data set. Moreover, the error term ϵ_i is by assumption correlated with the set of explanatory variables z_i, as x_i and y_i are correlated with z_i. This implies that conventional regression analysis cannot be applied to equation (D.16) as the basic assumption of error terms being identically and independently distributed is violated (Odeck, 2009). To overcome these limitations Simar and Wilson (2007) propose a procedure based on truncated regression models complemented by bootstrapping simulations. In our analysis we employ the following algorithm:

1. Computation of efficiency scores $\hat{\theta}_i$ for each DMU $i = 1, \ldots, L$ as described in Appendix D.2.
2. For all $\hat{\theta}_i > 1$ estimation of $\hat{\beta}$ and $\hat{\sigma}_\epsilon$ using a truncated regression of $\hat{\theta}_i$ on z_i.
3. In order to obtain a set of bootstrap estimates $A = \{(\hat{\beta}^*, \hat{\sigma}^*_\epsilon)_b\}_{b=1}^{L}$ loop over following steps L times:

(a) For each i draw ϵ_i from a $N(0, \hat{\sigma}_\epsilon^2)$ distribution with left truncation at $(1 - z_i\beta)$.

(b) For each i compute $\theta_i^* = z_i\hat{\beta} + \epsilon_i$.

(c) Estimation of $\hat{\beta}^*$ and $\hat{\sigma}_\epsilon^*$ using a truncated regression of θ_i^* on z_i.

4. Bootstrapped values in A and the original estimates of $\hat{\beta}$ and $\hat{\sigma}_\epsilon$ are used to construct estimated confidence intervals for each element of β and σ_ϵ.

D.5 Detailed Results

Table D.1: Annual Mean Efficiency Scores of City Banks (1999-2015)

	TE	PTE	SE	IRS	CRS	DRS
1999	1.114	1.108	1.005	0.00	0.78	0.22
2000	1.150	1.132	1.016	0.11	0.33	0.56
2001	1.141	1.122	1.017	0.14	0.43	0.43
2002	1.224	1.183	1.034	0.14	0.43	0.43
2003	1.182	1.159	1.019	0.29	0.43	0.29
2004	1.190	1.121	1.062	0.14	0.29	0.57
2005	1.166	1.127	1.035	0.00	0.33	0.67
2006	1.201	1.169	1.027	0.33	0.33	0.33
2007	1.195	1.144	1.043	0.33	0.33	0.33
2008	1.195	1.168	1.023	0.00	0.33	0.67
2009	1.168	1.158	1.008	0.33	0.33	0.33
2010	1.218	1.167	1.044	0.33	0.50	0.17
2011	1.155	1.157	0.998	0.00	0.50	0.50
2012	1.173	1.176	0.997	0.33	0.50	0.17
2013	1.167	1.143	1.021	0.00	0.40	0.60
2014	1.158	1.129	1.026	0.00	0.60	0.40
2015	1.155	1.127	1.026	0.40	0.40	0.20
Mean	1.172	1.146	1.023	0.17	0.43	0.40

Notes: Bias-corrected values based on the bootstrap procedure. TE is the technical efficiency score. PTE is the pure technical efficiency score. SE is the scale efficiency score. Values above unity indicate inefficiencies. IRS/CRS/DRS are the shares of banks operating under increasing/ constant/ decreasing returns to scale, respectively.

Table D.2: Annual Mean Efficiency Scores of Regional Banks I (1999-2015)

	TE	PTE	SE	IRS	CRS	DRS
1999	1.147	1.132	1.013	0.75	0.06	0.19
2000	1.149	1.140	1.008	0.58	0.13	0.29
2001	1.126	1.122	1.004	0.69	0.21	0.10
2002	1.069	1.074	0.996	0.64	0.14	0.21
2003	1.068	1.072	0.996	0.64	0.12	0.24
2004	1.080	1.084	0.996	0.79	0.10	0.11
2005	1.085	1.086	0.999	0.74	0.10	0.16
2006	1.103	1.102	1.001	0.79	0.06	0.15
2007	1.079	1.081	0.997	0.77	0.13	0.10
2008	1.130	1.126	1.003	0.80	0.03	0.17
2009	1.102	1.102	1.000	0.66	0.03	0.31
2010	1.135	1.129	1.005	0.74	0.03	0.23
2011	1.094	1.094	0.999	0.89	0.07	0.05
2012	1.082	1.087	0.995	0.65	0.10	0.26
2013	1.101	1.105	0.996	0.82	0.07	0.11
2014	1.102	1.105	0.997	0.64	0.14	0.22
2015	1.106	1.105	1.001	0.54	0.14	0.32
Mean	1.102	1.102	1.000	0.72	0.10	0.19

Notes: Bias-corrected values based on the bootstrap procedure. TE is the technical efficiency score. PTE is the pure technical efficiency score. SE is the scale efficiency score. Values above unity indicate inefficiencies. IRS/CRS/DRS are the shares of banks operating under increasing/ constant/ decreasing returns to scale, respectively.

Table D.3: Annual Mean Efficiency Scores of Regional Banks II (1999-2015)

	TE	PTE	SE	IRS	CRS	DRS
1999	1.159	1.151	1.007	0.92	0.00	0.08
2000	1.146	1.134	1.010	0.86	0.00	0.14
2001	1.134	1.128	1.005	0.84	0.03	0.13
2002	1.081	1.080	1.002	0.83	0.08	0.08
2003	1.077	1.076	1.001	0.79	0.03	0.18
2004	1.082	1.078	1.004	0.85	0.07	0.07
2005	1.092	1.085	1.007	0.93	0.05	0.03
2006	1.103	1.096	1.006	0.93	0.07	0.00
2007	1.086	1.082	1.004	0.90	0.10	0.00
2008	1.128	1.120	1.007	0.81	0.08	0.11
2009	1.104	1.098	1.006	0.81	0.08	0.11
2010	1.131	1.120	1.010	0.86	0.08	0.05
2011	1.103	1.092	1.011	0.93	0.05	0.03
2012	1.078	1.081	0.997	0.73	0.12	0.15
2013	1.097	1.095	1.002	0.87	0.08	0.05
2014	1.105	1.103	1.001	0.74	0.13	0.13
2015	1.110	1.105	1.004	0.70	0.11	0.19
Mean	1.105	1.099	1.005	0.84	0.07	0.09

Notes: Bias-corrected values based on the bootstrap procedure. TE is the technical efficiency score. PTE is the pure technical efficiency score. SE is the scale efficiency score. Values above unity indicate inefficiencies. IRS/CRS/DRS are the shares of banks operating under increasing/ constant/ decreasing returns to scale, respectively.

Table D.4: Annual Mean Efficiency Scores of Shinkin Banks (1999-2015)

	TE	PTE	SE	IRS	CRS	DRS
1999	1.290	1.246	1.037	0.96	0.02	0.02
2000	1.322	1.284	1.031	0.93	0.02	0.05
2001	1.313	1.278	1.028	0.95	0.03	0.02
2002	1.259	1.238	1.018	0.96	0.02	0.02
2003	1.262	1.238	1.019	0.95	0.01	0.04
2004	1.274	1.244	1.025	0.95	0.02	0.03
2005	1.283	1.249	1.028	0.96	0.01	0.02
2006	1.315	1.279	1.029	0.96	0.01	0.02
2007	1.312	1.263	1.040	0.97	0.01	0.01
2008	1.352	1.295	1.044	0.96	0.03	0.01
2009	1.326	1.273	1.041	0.96	0.02	0.01
2010	1.389	1.312	1.060	0.97	0.01	0.01
2011	1.373	1.308	1.051	0.99	0.01	0.00
2012	1.377	1.323	1.041	0.97	0.01	0.02
2013	1.399	1.344	1.042	0.97	0.01	0.01
2014	1.412	1.365	1.035	0.95	0.02	0.04
2015	1.394	1.338	1.045	0.92	0.02	0.06
Mean	1.331	1.286	1.036	0.96	0.02	0.02

Notes: Bias-corrected values based on the bootstrap procedure. TE is the technical efficiency score. PTE is the pure technical efficiency score. SE is the scale efficiency score. Values above unity indicate inefficiencies. IRS/CRS/DRS are the shares of banks operating under increasing/ constant/ decreasing returns to scale, respectively.

D.6 Robustness Checks

Previous studies on the efficiency of Japanese banks estimate efficiency scores for either commercial banks (e.g. Altunbas et al., 2000; Drake and Hall, 2003) or cooperative banks (e.g. Fukuyama and Weber, 2009; Assaf et al., 2011). In our analysis, however, we combine both types of banks to estimate Japanese banks' efficiency relative to the industry 'best practice' frontier and be able to compare the results between the different bank types. To check whether our regression results are sensitive to our sample choice we re-estimate TE, PTE and SE scores for two subgroups of banks: commercial banks (including city banks and both types of regional banks) and cooperative banks (including shinkin banks). We follow the procedure as described in Section 5.3. Separately for both subgroups, we regress the newly compiled efficiency scores on the set of explanatory variables described above.

The regression results for the subgroup of shinkin banks are shown in Table D.5. Previous findings for the standard control variables (MS, NPL, $ROAA$) and the variables capturing the effect of the low-interest rate environment and adjustment measures (NIM, $SECLOAN$, $GOVSEC$, $NIOI$) can be confirmed. Differing from the results of our baseline regression we find that an increase in bank size has a negative effect on both overall technical and pure technical efficiency. This implies that for the case of shinkin banks positive scale effects of an increased size did not outweigh the negative size effects on pure technical efficiency.

Table D.5: Robustness Check - Shinkin Banks

	(1) TE	(2) TE (ext.)	(3) PTE	(4) PTE (ext.)
MS	-0.8669***	-1.0906***	-0.9746***	-1.2228***
	[0.0851]	[0.0872]	[0.0950]	[0.0873]
NPL	0.0021***	0.0046***	0.0019***	0.0045***
	[0.0007]	[0.0007]	[0.0007]	[0.0006]
$ROAA$	-0.0134**	-0.0014	-0.0084	0.0043
	[0.0058]	[0.0058]	[0.0063]	[0.0060]
NIM		-0.2262***		-0.2375***
		[0.0107]		[0.0114]
$SECLOAN$		-0.0587***		-0.0570***
		[0.0096]		[0.0099]
$GOVSEC$		-0.0384***		-0.0533***
		[0.0128]		[0.0143]
$NIOI$		-0.0051		-0.0060
		[0.0046]		[0.0048]
$MEDBANK$	0.0135**	-0.0002	0.0583***	0.0485***
	[0.0062]	[0.0061]	[0.0070]	[0.0069]
$LARBANK$	0.0446**	0.0692***	0.0697***	0.1024***
	[0.0212]	[0.0229]	[0.0257]	[0.0299]
Constant	1.1408***	1.6837***	1.0858***	1.6546***
	[0.0132]	[0.0282]	[0.0146]	[0.0295]
Observations	4,096	4,086	3,856	3,854

Notes: $\widehat{TE}_{i,t}$ and $\widehat{PTE}_{i,t}$ are the dependent variables. All models estimated using a truncated regression model. Negative coefficients indicate positive effect on efficiency and vice versa. Reference category is $SMLBANK$. Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

The results for the group of city banks and regional banks are shown in Table D.6. Regarding the control variables, we find that positive market share effects are much smaller for the group of commercial banks than for shinkin banks. Furthermore, the coefficient of the non-performing loans ratio is statistically significant only in column (1). This implies that city banks and regional banks might have been better able to cope with the problem of non-performing loans than shinkin banks. Furthermore, our results confirm the negative effect of declining interest margins on banks' pure technical efficiency. In contrast to our findings from the baseline regression, a higher securities to loan ratio and a higher share of government securities is linked to declining overall technical efficiency and pure technical efficiency. The results confirm our previous findings that a larger bank size is linked to a decline in pure technical efficiency. Furthermore, we cannot confirm a statistically significant difference between the efficiency of city banks and regional banks.

Table D.6: Robustness Check - City Banks and Regional Banks

	(1) TE	(2) TE (ext.)	(3) PTE	(4) PTE (ext.)
MS	-0.0166**	-0.0076***	-0.1028***	-0.0560***
	[0.0079]	[0.0029]	[0.0301]	[0.0150]
NPL	-0.0052**	0.0007	-0.0039	0.0013
	[0.0023]	[0.0020]	[0.0029]	[0.0020]
$ROAA$	-0.0068	-0.0103*	-0.0107	-0.0102
	[0.0089]	[0.0061]	[0.0116]	[0.0062]
NIM		-0.0201		-0.0404**
		[0.0148]		[0.0163]
$SECLOAN$		0.2000***		0.1644***
		[0.0233]		[0.0222]
$GOVSEC$		0.0693***		0.0574**
		[0.0210]		[0.0231]
$NIOI$		0.0291		0.0300
		[0.0254]		[0.0243]
$LARBANK$	-0.0201*	-0.0244***	0.1037***	0.0075
	[0.0105]	[0.0074]	[0.0174]	[0.0084]
$HUGBANK$	-0.0223	-0.0078	0.1789*	0.0630*
	[0.0494]	[0.0254]	[0.0922]	[0.0356]
RBI	-0.0249	0.0102	-0.0705	-0.0201
	[0.0486]	[0.0248]	[0.0697]	[0.0300]
$RBII$	-0.0339	0.0342	-0.1006	0.0008
	[0.0491]	[0.0268]	[0.0724]	[0.0319]
Constant	1.8721***	1.7259***	1.7099***	1.7272***
	[0.0525]	[0.0529]	[0.0776]	[0.0611]
Observations	1,568	954	1,438	844

Notes: $\widehat{TE}_{i,t}$ and $\widehat{PTE}_{i,t}$ are the dependent variables. All models estimated using a truncated regression model. Negative coefficients indicate positive effect on efficiency and vice versa. Reference categories are $MEDBANK$ and CB. Standard errors in parentheses *p <0.1, **p <0.05, ***p <0.01.

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Selbständigkeitserklärung

Hiermit erkläre ich, die vorliegende Dissertation selbständig und ohne unzulässige fremde Hilfe, insbesondere ohne die Hilfe eines Promotionsberaters, angefertigt zu haben. Ich habe keine anderen als die angeführten Quellen und Hilfsmittel benutzt und sämtliche Textstellen, die wörtlich oder sinngemäß aus veröffentlichten oder unveröffentlichten Schriften entnommen wurden, und alle Angaben, die auf mündlichen Auskünften beruhen, als solche kenntlich gemacht. Ebenfalls sind alle von anderen Personen bereitgestellten Materialien oder erbrachten Dienstleistungen als solche gekennzeichnet.

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Bibliographische Beschreibung

Gerstenberger, Juliane

Impacts of the Low-Interest Rate Policy on the Corporate Sector

Universität Leipzig, Dissertation
184 S., 256 Lit[41], 35 Abb., 51 Tabellen

Referat:
Die Dissertation untersucht die Folgen der Niedrigzinspolitik für den Unternehmenssektor und besteht aus vier eigenständigen Aufsätzen.

Im ersten Aufsatz "Is the Interest Rate Channel still working? Post-Crisis Evidence from German SMEs" wird der Zusammenhang von Kapitalkosten und Unternehmensinvestitionen untersucht. Es wird gezeigt, dass Unternehmen mit pessimistischen Geschäftserwartungen weniger sensitiv auf Kapitalkostenänderungen reagieren.

Im zweiten Aufsatz "Declining Interest Rates and German SMEs' Use of Bank Debt" wird der Zusammenhang von Zinsänderungen und der Kreditnachfrage von Unternehmen untersucht. Es wird gezeigt, dass fallenden Zinsen zu einem Rückgang der Kreditnachfrage beitragen können.

Im dritten Aufsatz "Impaired Capital Reallocation in a Low-Interest Rate Environment – Evidence from German SMEs" werden die Folgen der Niedrigzinspolitik für die effiziente Allokation von Kapital im Unternehmenssektor untersucht. Es wird gezeigt, dass der Produktivitätsrückgang im deutschen Unternehmenssektor u.a. auf eine Missallokation von Kapital zurückgeführt werden kann.

Im vierten Aufsatz "The Impact of the Bank of Japan's Crisis Management on the Japanese Banking Sector" werden die Folgen der Geldpolitk der Bank of Japan für den japanischen Bankensektor untersucht. Es wird gezeigt, dass die geldpolitischen Rettungsmaßnahmen zu einem Rückgang der Effizienz im Bankensektor beigetragen haben.

[41] Anzahl der in den Literaturverzeichnissen der Kapitel angegebenen Literaturangaben insgesamt. Keine Doppelzählung.